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Defaults and Donations: Evidence from a Field Experiment*

Steffen Altmann, Armin Falk, Paul Heidhues, Rajshri Jayaraman, and Marrit Teirlinck

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ABSTRACT

We study how defaults affect charitable donations. In a field experiment that was conducted on a large online platform for charitable giving, we exogenously vary the default options in the donation form in two distinct choice dimensions. The first pertains to the primary donation decision, namely, how much to contribute to the charitable cause. The second relates to a "codonation" decision of how much to contribute to supporting the online platform itself. We find a strong impact of defaults on individual behavior: in each of our treatments, the modal positive contributions in both choice dimensions invariably correspond to the specified default amounts. Defaults, nevertheless, have no significant effects on average donation levels. This is because defaults in the donation domain induce some people to donate more and others to donate less. In contrast, higher defaults in the secondary choice dimension unambiguously induce higher average contributions to the online platform. We complement our experimental results by setting up and estimating a structural model that explores whether personalizing defaults based on individuals' donation histories can help the online platform to increase donation revenues.

Keywords: Default Options, Online Platforms, Charitable Giving, Field Experiment

JEL codes: D03, D01, D64, C93

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1. Introduction

Online fundraising constitutes a sizable and rapidly growing segment of the market for charitable giving.[1] A pervasive feature on the websites of charities and online fundrasising platforms are default options that specify the amount to be donated unless a donor actively enters a different contribution level. The ubiquity of default donation amounts in online fundraising is likely to stem from a common presumption that "defaults matter". This presumption—buttressed by famously documented examples of the importance of defaults for decisions on retirement saving or organ donation (e.g., Madrian and Shea 2001, Johnson and Goldstein 2003, Thaler and Sunstein 2008)—has generated a lively discussion in the practitioner community regarding "best practice" for setting default donation amounts. Yet, this discussion lacks rigorous evidence.[2]

This paper takes a step towards closing this evidence gap with the help of a natural field experiment on Germany's largest online platform for making charitable contributions. The experiment is designed to ask two main questions. First, do defaults affect individual behavior; in other words, do they influence the distribution of individuals' contributions? Second, do defaults influence overall donation revenues?

To address these questions, we exogenously vary default options in two distinct choice dimensions: The main donation decision and an add-on choice, which is a gratuity to support the providers of the online platform. Regarding the first dimension, website visitors are randomly assigned to default donation amounts of €10, 20, and 50. These values correspond, respectively, to the 25th, 50th, and 75th percentile of donations on the platform in the six months prior to our experiment. This allows us to examine whether defaults have stronger or weaker effects on behavior when they are set relatively high or low compared to what most people would donate otherwise. We also implement an additional treatment in which the donation field is initially set to zero, such that

[1] In 2017, online giving accounted for 7.6% of the total—multi-billion—fundraising volume in the U.S. nonprofit sector (see Blackbaud 2018). In line with the positive trend from previous years, online giving grew strongly both in absolute terms as well as compared to the overall increase in charitable giving (the yearly growth rates were 12.1% and 4.1%, respectively).

[2] Perhaps the best existing evidence comes from a disaster relief donation drive conducted by Google.com in 2009 (see http://googlecheckout.blogspot.dk/2009/12/google-checkout-for-non-profits-in-2010.html). While there is no information on sample sizes and statistical significance, the results indicate that—with the exception of a strong drop in average donations at a $20 default—overall donation revenues did not differ strongly for different default donation levels.

people who want to make a donation have to make an active decision on their contribution level. In our second treatment dimension, we randomly assign donation-page visitors to percentage add-ons of 5%, 10%, or 15% of their main donation. The corresponding contributions, or "codonations", are used to support and maintain the online platform, which itself operates as a nonprofit organization.

Over the course of our experiment, we collected data on roughly 680,000 donation-page visits and almost 23,000 donations, yielding a total of €1.17 million in terms of revenues for charitable organizations on the platform. Our data show that defaults have a strong impact on individual donor behavior. In each of our treatments, the modal positive contribution invariably corresponds to the default specification. This holds for the main donation decision as well as for the add-on contribution to the online platform, indicating that defaults are important poles of attraction for donors' behavior in both decision dimensions.

Despite these systematic effects on the distribution of donations, defaults in our experiment do not significantly alter overall donation revenues. We neither find systematic differences in average contributions across the different donation defaults, nor when comparing average donation levels to the environment where donors have to actively decide on their contribution. The difference between our individual- and aggregate-level results can be explained by countervailing changes in the distribution of donations due to defaults. We find that, relative to the active-decision environment, defaults induce some people to donate more while others donate less or not at all, such that the two countervailing effects cancel each other out at the aggregate level. For default contributions of €10 and €20, the changes in the donation distribution operate entirely on the intensive margin. At the €50 default, we observe an additional extensive-margin effect, with more people opting out of the donation process altogether. As a result of this higher donor attrition, average donations once again do not differ significantly from those in the other treatments. By contrast, we do observe strong average treatment effects in the add-on dimension. Average codonation revenues increase monotonically in the percentage add-on that is set as the default. This is because the dominant change in the distribution of codonations at higher default values is an intensive-margin movement towards the default from lower codonations.

In the final part of our empirical analysis, we examine whether "personalized" defaults could help to raise donation revenues in our setting. We start by exploring heterogenous treatment effects based on individual-level characteristics such as gender and the type of donation. Consistent with a number of earlier findings in the literature (e.g., Madrian and Shea 2001, Levav et al. 2010, Altmann, Falk, and Grunewald 2013), we find that some groups of donors are more likely to stick to defaults than others. Our reduced-form estimates, however, also indicate that there is little scope for making use of this tendency to systematically increase donations. To further explore whether the online platform could increase donations by differentiating defaults based on individuals' prior donation levels, we estimate a simple structural model in which individuals behave *as if* deviating from the default were costly (motivated by Carroll et al. 2009 and Bernheim, Fradkin, and Popov 2015). Counterfactual simulations based on our model estimates indicate that there is at best modest scope for successfully using personalized defaults in a setting like ours, in which information on (potential) donors is sparse.

Related Literature. Our paper contributes to two main strands of the literature. First, we add to the body of literature that analyzes the impact of defaults on a variety of economic decisions, such as retirement saving (e.g., Madrian and Shea 2001, Beshears et al. 2008, and Carroll et al. 2009), organ donor registration (e.g., Johnson and Goldstein 2003 and Abadie and Gay 2006), or the choice of insurance contracts (Johnson et al. 1993).

An important difference between the mentioned studies and ours is that they consider applications in which consumers who remain entirely inactive automatically stick to the default. In contrast, potential donors in our setting must actively confirm the transaction for the default to affect outcomes. This is similar to how default options are used in web interfaces for configuring computers, cars, and other customizable products (e.g., Levav et al. 2010, Ebeling 2013). As we explain in Section 3.4, the difference between the two types of settings is important, as some common explanations for default effects—such as procrastination in making choices—are unlikely to play an important role for our results. These differences notwithstanding, we find that the workhorse model for capturing default effects in the retirement savings literature—a model involving fixed costs of deviating from the default (see, e.g., Carroll et al. 2009 and Bernheim, Fradkin, and Popov 2015)—does remarkably well in fitting the key features of the donation distributions in our experiment. At the same time, our estimates indicate that in our setting a much smaller fraction of potential donors is affected by these as-if costs, which is in line with the intuition that procrastination is indeed an important factor behind the default effects observed in the retirement savings context (e.g., Carroll et al. 2009).

Our experiment differs from previous studies on "web defaults" in other economic applications (e.g., Johnson, Bellman, and Lohse 2002, Löfgren et al. 2012, Ebeling 2013) in that we examine a setup where consumers do not only face a binary opt-in vs. opt-out decision, but have a continuum of decision alternatives. This allows us to study a rich set of reactions to defaults along both the intensive and extensive margin of the donation distribution. Our findings demonstrate that defaults can have manifold—and, in our case, countervailing—effects, highlighting the importance of a detailed assessment of distributional effects of defaults for non-binary choices. In particular, our results indicate that a strategy that attempts to boost donation revenues through higher defaults based on a simplistic notion that "defaults work" might backfire for charitable organizations.[3]

The second strand of the literature to which our paper contributes is that on charitable giving and nonprofit fundraising. While defaults are widely observed on online donation platforms and many practitioners presume that appropriately specified defaults will help them increase donations, there has been a lack of rigorous evidence on the causal effects of default options on donation behavior. A notable exception are two recent papers by Fiala and Noussair (2017) and Goswami and Urminsky (2016), who study default effects on charitable giving in lab experiments and online surveys, with mixed results: while Fiala and Noussair (2017) observe no significant differences in overall donation levels under different defaults, Goswami and Urminsky (2016) report a small positive effect of higher defaults. One has to bear in mind, however, that these findings are based on relatively small samples and arguably rather weak incentives.[4]

[3]This is related to a recent result by Haggag and Paci (2014), who analyze tipping behavior in New York City cabs and find that customers are more likely to leave no tip at all when the payment interface features a high default tip.

[4]More distantly related, Smith and Ottoni-Wilhelm (2018) document that default values systematically affect fundraisers' choices of fundraising goals. Analyzing voluntary cooperation outside a charitable-giving context, Messer et al. (2007), Altmann and Falk (2011), and Fosgaard and Piovesan (2015) examine the effects of defaults in laboratory public goods games, and find that that higher default contribution levels tend to enhance cooperation, at least in early periods of the game.

Beyond defaults, a voluminous literature has examined the impact of other fundraising interventions (see Andreoni 2006 as well as Bekkers and Wiepking 2011 for comprehensive reviews of the literature). Our paper is related to these studies in that some of the potential mechanisms behind default effects can also play a role for other fundraising interventions. Specifically, to the extent that potential donors interpret the default option as a recommended contribution to the charitable cause, our paper is related to studies that examine how giving is affected by directly requesting (Fraser, Hite, and Sauer 1988, Edwards and List 2014) or explicitly suggesting (Adena, Huck, and Rasul 2014, Goswami and Urminsky 2016) specific donation levels during solicitation. Similarly, the literature on "appeal scales" (i.e., providing donors with a vector of multiple suggested contribution levels; see, e.g., Weyant and Smith 1987, Desmet and Feinberg 2003, Adena and Huck 2016, and Reiley and Samek 2017) is related in that there is a partial overlap in the channels through which appeal scales and defaults may affect behavior (e.g., recommendations or anchoring). Lastly, interventions based on statements like "every penny helps" (e.g., Cialdini and Schroeder 1976, Fraser, Hite, and Sauer 1988) or the provision of information about other donors' behavior (e.g., Frey and Meier 2004, Shang and Croson 2009) are potentially related to defaults, as they may also affect behavior by transmitting information or shaping social norms. Since all of these interventions, however, also introduce aspects that are unrelated to defaults[5] and since defaults, in turn, may work through mechanisms that have little or no relevance for the other interventions, it is difficult to directly compare the results of these studies to our setting.

The paper proceeds as follows. In the next section, we describe the setup, treatments and procedures of our experiment. Section 3 presents the main results of our experiment, and Section 4 examines whether the charity could increase aggregate donation revenues by personalizing defaults. Section 5 concludes.

2. The Experiment

2.1. **The Donation Platform.** We study the effect of default options on betterplace.org, Germany's largest platform for making charitable donations over the web. At the time of the

[5]For instance, the studies on explicit requests typically provide additional contextual information or employ relatively strong framing. Similarly, appeal scales open the possibility for "decoy" or "compromise effects" (e.g., Simonson 1989, Ekström 2018).

experiment, the platform hosted about 6,000 "project pages" through which charities collect funds for their activities. The aid projects on the platform cover the whole gamut in terms of geography, charitable cause, and scale. They range from after-school help for a handful of children in Berlin, to supporting orphanages in Kenya, to humanitarian aid for victims of natural disasters. Charities that are present on Betterplace include small local NGOs as well as organizations like UNICEF or the International Committee of the Red Cross. The platform also hosts pages for "fundraising events", which offer individuals, firms, or other organizations the possibility to collect donations for one of the aid projects by organizing charity runs, benefit concerts, or similar fundraising campaigns.

Visitors to the donation platform can browse individual fundraising or project pages, which describe the project and overall budget needed to fund it, as well as the amounts of money that are required for the specific elements of which the overall project consists. Figure 1 provides an example of a project page. (A full English translation of the original screen shot can be found in Figure B.1 of the online appendix.) The project title, "Typhoon Haiyan: Emergency Relief in the Philippines", is displayed at the top of the page, followed by a picture, a location map, and a project description. The number of previous donors, the proportion of the overall project budget that has already been funded, and the amount that is still required for the project are displayed in the upper right part of the page. Potential donors can contribute directly to the aid project or to one of the specific project elements, in this example relief packages for the catastrophe zone, displayed at the bottom right of the figure and further below on the screen (suppressed in Figure 1).[6]

By clicking on either of two red buttons on the screen—the large button, which reads "Jetzt spenden" translates to "Donate now" and the smaller one at the bottom right, which reads "Hierfür spenden" translates to "Donate for this"—the potential donor is redirected to the donation page for the project (Figure 2; see Figure B.3 in the online appendix for a full English translation). On this page, the donor specifies the amount that she wishes to contribute to the charitable cause, by filling in the "Project donation" ("Projektspende") field on the top left part of the screen. In what follows, we refer to this amount as the *donation* or *donated amount*.

[6]The corresponding page for fundraising events has a slightly different layout (see Figure B.2 in the online appendix for an example). The donation page on which our experimental intervention takes place, however, is exactly the same for all types of donations (see Figure 2).

FIGURE 1. Screen shot of a project page.

In addition to specifying the donation to the charitable cause, donors can also make a contribution to support the online platform. In this secondary choice dimension, contributions can be determined as a percentage add-on or as an absolute Euro amount that is added to the project donation. By clicking the field below the "Support betterplace.org" ("Fördere betterplace.org") label on the right side of the screen, a drop-down menu appears that allows donors to choose between the options "not this time" (i.e., no contribution), 5%, 10%, 15%, 20%, 25%, or "other amount". The last of these options gives the donor the possibility to enter any absolute Euro amount. We refer to the add-on contributions in support of the platform as *codonations*. Codonations are used to cover the costs for developing and sustaining the platform, which itself operates as a nonprofit organization.

The sum of the donation and codonation amount determine the donor's "Total donation" ("Gesamtspende"), which is automatically calculated in the second line on the left of the donation form. In the bottom part of the donation page (suppressed in Figure 2), donors are asked to provide further information that is required to finalize the transaction, including their name and payment details. After having completed the donation form, donors confirm the transaction by clicking a "Donate Now" button at the end of the page.

FIGURE 2. Screen shot of the donation page.

2.2. **Treatments.** Our experimental intervention pertains to the donation page depicted in Figure 2. For each website visitor who enters the donation page, we exogenously vary the donation and codonation amounts that are displayed by default in the respective fields of the donation form. We randomize independently in the two different treatment dimensions. In the *donation dimension*, we assign potential donors to one of four different treatments. Specifically, when arriving at the donation page, the amount displayed in the project donation field is either zero, or corresponds to a pre-specified donation level of €10, €20, or €50. Note that in each case, donors are free to contribute any positive amount by simply typing in the desired contribution level into the project donation field.

The three positive default values correspond, respectively, to the 25th, 50th, and 75th percentile of all donations on the platform during the six months before our experiment started. This allows us to examine whether defaults have stronger or weaker effects on behavior when they are set relatively high or low compared to what most people would donate otherwise.[7] In contrast to the positive donation defaults, the zero treatment implements an active-decision or "forced-choice" environment: A user who wants to make a donation in this treatment has to actively specify the amount she wishes to contribute. If a donor tries to finalize the transaction while the donation field is set to zero, an error message appears and the donor is redirected to the donation form. Active-decision environments are sometimes argued to have desirable properties, e.g., if preferences in the

[7]Coincidentally, rather than by design, the different default amounts also correspond to modes in the historical distribution of donations (as well as in the active-decision environment). This is the case since—as we will see in further detail in Section 3—many donors contribute "round" or "prominent" amounts such as €5, €10, €20, etc. It is unclear whether this may dampen or magnify the impact of defaults on behavior. On the one hand, defaults may have little traction to increase the mass of donations at these modes, given that relatively many people are already giving these amounts. On the other hand, it may be easier for defaults to attract potential donors from more "unusual" donation levels to the common default amounts (e.g., follow a default of €10 or €20 instead of giving €14), or to make potential donors "jump" from one prominent amount to another.

population are very diverse (see Carroll et al. 2009 or Sunstein 2013). In our empirical analysis below, this treatment will provide us with a benchmark of actively determined donations, against which we can compare donors' behavior in the treatments with positive donation defaults.

There is a second sense in which our setting involves active decision-making: contributions, and thus potentially also the default donation levels, only become effective after users actively confirm the transaction. While this is typical for how defaults—or, more specifically, "default options"—are implemented in a wide variety of online applications, it differs from the use of defaults in other settings like organ donor registration or 401(k) savings plans. In these environments, defaults—or what might be coined "default rules"—are typically implemented as a set of rules that are relevant for the decision maker even if she remains entirely passive. While this difference may seem subtle, it is potentially important for understanding the channels through which defaults can affect behavior. In particular, as we will discuss in further detail in Section 3.4 below, the degree to which present-biased preferences and procrastination of active decisions might affect outcomes differs between the two different types of default regimes.

In our second treatment dimension, *codonations*, we independently vary the pre-specified percentage add-on to support the online platform. Specifically, we randomly assign donation-page visitors to codonation defaults of 5%, 10%, or 15%. These treatments were chosen based on historical values and heuristics. The 5% default was the value originally used by the platform. It was retained in the experiment as a "control" group representing the status quo before the beginning of the intervention. The remaining two values were chosen based on the intuition that the codonation is likely to be perceived as a "tip" to Betterplace. The codonation defaults of 10% and 15% were implemented as they correspond to the tipping conventions in Germany and places like North America, respectively.

2.3. **Implementation of the Experiment.** The experiment was conducted over an 11-month period from June 08, 2012 to April 19, 2013. Overall, we observe roughly 680,000 donation-page visitors during this period, distributed over the 12 different treatment cells in our 4×3 design (see Table 1 for an overview). Some aspects of our data and procedures are worth noting. First, to avoid technical errors in the settlement of payments, our experiment is confined to situations where the remaining required budget for the respective project element is at least €50 (i.e., the highest possible default). Second, to rule out that a small number of extreme contributions may distort our results, we drop the top 0.2% of donors (n=41) for our empirical analysis.[8]

Third, we randomize website visitors into treatments at the "website-session" level, such that they remain in the same treatment throughout their visit to the platform. This minimizes the possibility that a potential donor who visits more than one donation page—because she wishes to make multiple donations or browses several project and donation pages before ultimately making a donation decision—is exposed to different treatments. More precisely, we assign treatments when a user enters a donation page for the first time. Subsequently, a browser cookie ensures that the user keeps being exposed to the same treatment. While we cannot perfectly ensure that a donor never faces another treatment (e.g., when she makes donations from two different computers), this procedure minimizes donors' awareness of the experiment and possible treatment spillovers.

Donation default	Codonation default 5%	10%	15%	Total
AD	56,894	56,959	56,807	170,660
€10	56,739	57,014	57,017	170,770
€20	56,777	57,083	57,117	170,977
€50	57,183	56,985	57,335	171,503
Total	227,593	228,041	228,276	683,910

TABLE 1. Treatments and number of observations per treatment. *Notes:* "AD" denotes the active-decision environment.

Our final sample covers 683,910 observations—roughly 57,000 in each of the 12 treatment cells (see Table 1). In 99.7% of cases, one observation in the table corresponds to a unique website visitor or "session": the 683,910 observations correspond to 681,660 unique sessions. This is the case since relatively few donors make more than one donation during our observation period. Table A.1 in the appendix indicates that observations are balanced in terms of baseline characteristics for which we have information, namely whether the potential donation was for a fundraising event, a

[8]Each of these donors contributes €2,165 or more. This compares to a median donation level of €20. Some of the figures reported below (e.g., the exact values of the average donation and codonation amounts) naturally depend on the specific cutoff used. Unless explicitly noted otherwise, however, our main results and conclusions remain unchanged when applying different cutoff levels (e.g., excluding the top .1%, .5%, or 1% of donors).

project, or an element within the project, and whether or not potential donations to a given project are tax deductible (which is typically the case when the charity is registered in Germany).

In total, we observe 22,792 donations coming from 20,542 different participants. Among those who do make a positive donation, 92.5% (n=19,010) make a single donation in the period of our intervention, 5.5% (n=1,125) make two donations, and the remaining 2% (n=407) make 3 or more donations. In what follows, we separately include the different individual donations as our unit of analysis for participants who make multiple donations within a session. To control for possible dependencies of observations, all estimation results reported below are clustered at the website-session level. This clustering has almost no bearing on our empirical findings. Results are also robust to using alternative approaches to account for donors with multiple contributions (e.g., using the sum of donations or focusing only on the first decision for each donor).

Table 2 provides an overview of the fraction of participants who make a donation (denoted as the "donation rate" in what follows), the amount donated to the charitable cause, and the amount of codonations (for a more detailed overview of summary statistics by treatment, see Table A.1 in the appendix). Over the course of the experiment, we observe 22,792 donations, corresponding to an overall donation rate of 3.33%. At first glance, this rate seems relatively low, given that participants in our experiment are all individuals who visited the online platform, browsed through the website and, at least at some point, clicked on the "Donate Now" button. According to the platform providers, however, this figure is in line with historical levels of the donation rate on the platform. Relatively low donation rates are common in the charitable-giving literature in general (see, e.g., Karlan and List 2007, Falk 2007, Huck and Rasul 2011), and in online fundraising more specifically. In a study based on the online fundraising sites of 84 nonprofit organizations, for instance, M + R Benchmarks (2015) reports a median overall conversion rate on the charities' websites of 0.76%. Conditional on visiting the organizations' main donation page, the median donation rate reported in the study is 13%. We can only speculate on what drives the relatively lower donation rate in our setting, compared to the last figure. One possible explanation is that we are studying a "marketplace" for charitable projects where platform visitors may have more diffuse donation intentions compared to potential donors who visit the website of a specific charitable organization. The latter might also attract a relatively higher fraction of donors who arrive at the website in response to solicitation emails or other fundraising drives of the charity. Indeed, we also observe considerably higher donation rates for participants who come to the platform through an organized "fundraising event" (see Section 2.1); in this case, donation rates are roughly 10-11%.[9]

As a consequence of the low donation rate, the modal action of participants in our experiment is not to donate. This holds for all of our treatments (see Table A.1 in the appendix). Conditional on making a donation, the average (median) donation level in our sample is €51.27 (€20). The corresponding values for codonations are €2.00 and €0.25, respectively. In sum, these numbers yield a total of €1.17 million in terms of donations and roughly €45,500 in codonations over the course of our experiment.

Variable	No. Obs.	Mean	Median	SD
Donation rate	683,910	0.033	0.00	0.18
Donation amount	22,792	51.274	20.00	117.17
Codonation amount	22,792	1.998	0.25	7.02

TABLE 2. Summary Statistics.

3. EMPIRICAL RESULTS

In this section, we present the result of our experiment. We begin, in Section 3.1, by studying treatment effects in terms of individual donor behavior. In particular, we analyze how the different defaults affect the distributions of donations and codonations in the experiment. In Sections 3.2 and 3.3, we turn to an aggregate-level perspective and examine the influence of defaults on average donation and codonation revenues, respectively. We also explore how treatment differences on the intensive and extensive margin of the donation and codonation distributions can account for the observed aggregate-level outcomes. We conclude, in Section 3.4, by discussing which psychological mechanisms may account for donors' reactions to defaults in our experiment.

[9]Reassuringly, our main findings (i.e., strong distributional effects for both donations and codonations, but significant average treatment effects only in terms of codonations) hold both for participants who respond to fundraising events as well as those who visit the donation pages of aid projects or project elements. Our empirical analysis in Section 3 thus concentrates on the pooled data set that includes all participants. In those cases where we find systematic differences between different donor types for more specific results, we note this explicitly.

3.1. **Do Defaults Affect Individual Donor Behavior?** In a first step, we examine how defaults influence individual donation and codonation patterns across treatments. Does the presence of defaults lead to systematic bunching of donors at the respective default amounts? The answer to this question is a clear yes. To illustrate this point, we examine the distributions of donations and codonations, focussing first on the 22,792 cases in which participants in our experiment actually make a donation. Table 3 summarizes the distribution of donations across treatments. Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for the donation amount and codonation percentage, (d€, c%). In the rows of the table, we depict the fraction of donations in a given treatment that correspond to one of the default donation levels, €10, €20, and €50, as well as the fraction of donations that differ from these values.

The highlighted cells reveal a strong impact of defaults on individual donations. The likelihood of making a donation of €10, €20, or €50 is considerably more pronounced when the respective amount is selected as the default donation level. For instance, 22.9%, 22.8%, and 21.7% of donors make a contribution of €10 in the three treatment cells where this amount is the default donation value (see columns 1-3 of Table 3). This compares to only 12-14% of donors making a €10-contribution when facing a default of €20 or €50 (columns 4-9). Similar effects can be found for each of the nine treatments that involve a positive default contribution. Comparing the highlighted fractions of donors who stick to the different defaults to the corresponding numbers in the treatments where donors have to make an active decision (AD in columns 10-12) shows that setting the default to a certain value increases the proportion of donors who actually contribute this amount by roughly 5-10 percentage points. Given that the observed baseline values for the different donation levels in the active-decision environment lie between 10 and 17%, this implies that defaults increase donors' propensity to make the corresponding contribution by 30-90%.

	Treatment (d€, c%)											
	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)	(AD,5)	(AD,10)	(AD,15)
Donated amount	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
€10	**.229**	**.228**	**.217**	.128	.128	.124	.135	.139	.132	.173	.164	.146
€20	.124	.109	.114	**.233**	**.211**	**.238**	.105	.109	.110	.119	.124	.132
€50	.106	.115	.104	.094	.110	.095	**.196**	**.183**	**.176**	.122	.115	.122
other	.541	.549	.565	.546	.552	.544	.564	.569	.582	.586	.597	.600

TABLE 3. Donations by treatment. *Notes:* The table depicts the proportion of donors in a given treatment who contribute €10, €20, or €50, as well as the fraction of donors who donate a different amount ("other"). Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for donations / codonations.

	Treatment (d€, c%)											
	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)	(AD,5)	(AD,10)	(AD,15)
Codonation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
0	.421	.451	.439	.413	.432	.448	.426	.495	.475	.455	.480	.486
5%	**.530**	.138	.121	**.532**	.147	.133	**.530**	.121	.141	**.502**	.125	.144
10%	.033	**.385**	077	.023	**.399**	.082	.022	**.363**	.071	.022	**.373**	.071
15%	0	.003	**.337**	.003	.002	**.308**	.001	.005	**.290**	.001	.003	**.280**
other	.017	.024	.027	.029	.020	.030	.021	.017	.023	.020	.020	.019

TABLE 4. Codonations by treatment. *Notes:* The table depicts the proportion of donors in a given treatment who make a codonation of 0, 5%, 10%, 15%, as well as the fraction of donors who codonate a different amount ("other"). Each column in the table corresponds to a different treatment cell, denoted by the corresponding default values for donations / codonations.

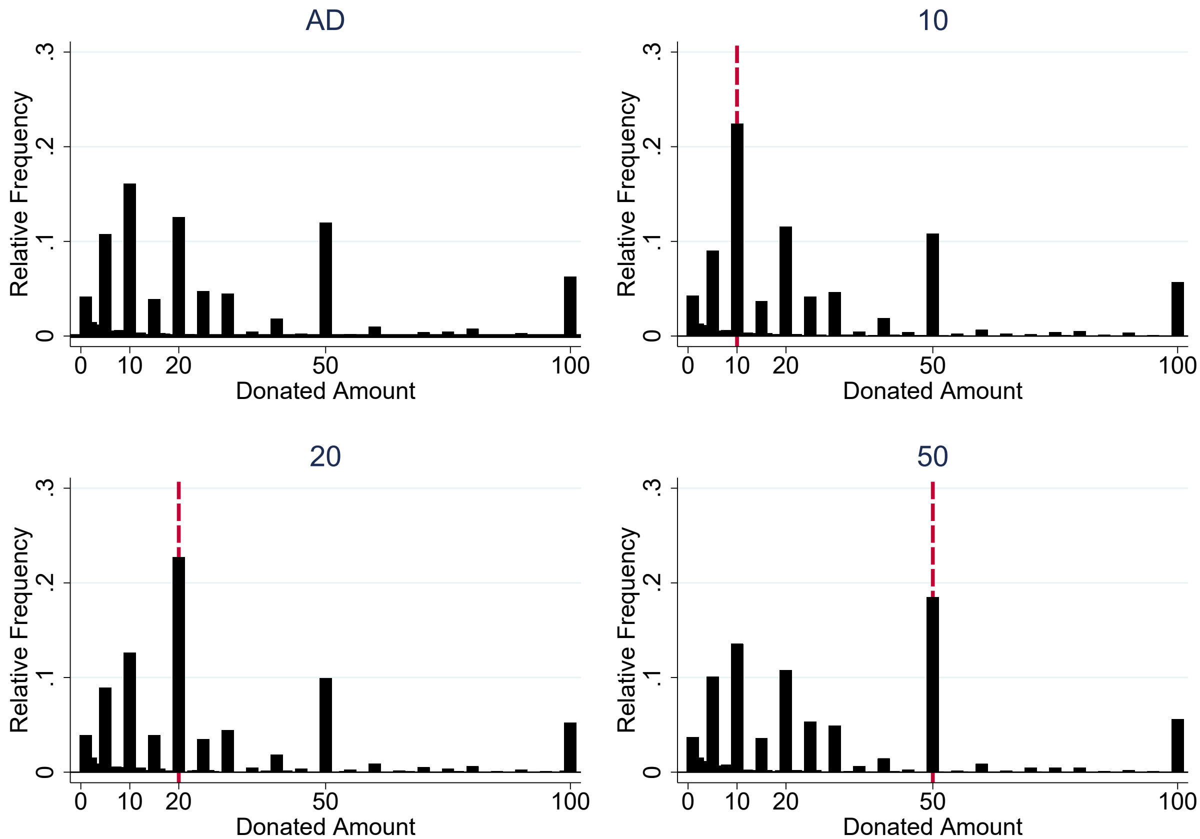


FIGURE 3. Donation distributions by default donation level. *Notes:* The figure depicts the relative frequencies of donations for each of the treatments in the donation dimension (indicated by the panel titles). Default donation levels are highlighted by the dashed lines. The x-axes of the graphs are censored at €100 (the underlying data are not).

The strong influence of defaults on individual donor behavior is also evident in the overall distribution of donations. In Figure 3, we present histograms for the active-decision regime and the three different donation defaults. To facilitate illustration, we right censor the x-axis of the graphs at €100 and focus our attention on the donation-default dimension. More precisely, we plot the histograms for subsamples in which we pool observations across the different codonation treatments, holding the treatment assignment in the donation dimension constant.

The histograms underscore the strong impact of defaults on donation patterns. While the distributions otherwise look relatively similar—e.g., we observe more or less pronounced spikes in donations at multiples of €5—there is a marked difference in the proportion of donations at the default values (indicated by the dashed lines). Indeed, the figure shows that the modal contribution always corresponds to the default donation level. Kolmogorov-Smirnov tests indicate that the distributions of donations differ significantly across the four different default regimes (p<0.01 for all pairwise tests).

The systematic influence of donation defaults on the distribution of donations is also evident when considering the 12 individual treatment cells separately. Figure B.4 in the online appendix depicts the full set of histograms for all individual treatment cells. When comparing the distributions of treatment pairs that differ in terms of donation defaults, but have identical codonation defaults (i.e., when testing across "columns" within a given "row" of Figure B.4), all but one treatment comparisons are statistically significant (p=0.138 when comparing (AD,5) vs. (10,5); p<0.05 for all other pairwise treatment comparisons). At the same time, the distributions of donations generally do not differ significantly when holding the donation default constant, but varying the default in the codonation dimension (i.e., comparing the rows within a given column of Figure B.4): only one out of twelve pairwise treatment comparisons turns out to be significant at the 10% level (Kolmogorov-Smirnov tests; p=0.084 when comparing the (20,5) and (20,10) treatments).

In a next step, we study how defaults affect behavior in our second treatment dimension—the add-on contribution to support the online platform. Table 4 depicts the codonation frequencies across treatments, mirroring the analysis of donations in Table 3.[10] The highlighted cells indicate that defaults also have a pronounced impact on individuals' behavior in terms of add-on contributions. For instance, moving from a 5% to a 10% default increases the proportion of donors who make a 10% contribution from roughly 2-3% to 35-40% (see the third row of Table 4). Another noteworthy feature of Table 4 is that participants' choices in the codonation dimension exhibit a bimodal pattern, with 40-50% of donors in a given treatment making no codonation at all and another 30-50% of donors sticking exactly to the respective default amount. Comparing differences in the distributions of codonations using Kolmogorov-Smirnov tests shows that the distributions

[10] The corresponding codonation histograms can be found in Figure B.5 in the online appendix. We display individual treatment cells instead of histograms for subsamples that pool across donation defaults, since Kolmogorov-Smirnov tests indicate a number of significant differences between individual distributions (e.g., the codonation distribution for the (10,15) treatment in the third row of Figure B.5 turns out to differ significantly from the (AD,15) as well as the (50,15) treatment; p<0.01 in both cases).

differ significantly for all pairwise tests of individual treatments that differ in the codonation default, but have the same default donation (p<0.01 in all cases).

Our data also indicate that donors' propensity to stick to defaults in the two different choice dimensions is highly correlated. In particular, the conditional likelihood of donating the default amount is almost 80% higher for donors who also stick to the default in the codonation dimension (the respective likelihoods are 28.7% vs. 16.1%; p<0.01). This suggests that some people in our sample are systematically more affected by defaults than others. It is not to say, however, that we generally observe no default effects for those participants who actively deviate from the default in one of the decision dimensions. For instance, among donors who actively opt out of the codonation default, we still observe bunching at the default for donations: relative to the active-decision environment, their propensity to donate the stipulated default amount increases by 10-40%.[11] We will return to the discussion of "types" that are generally more likely to stick to defaults in Section 4.

3.2. **Do Defaults Affect Average Donation Levels?** In a next step of our analysis, we explore how defaults affect average donation amounts at the aggregate level. Figure 4 presents average donation levels across treatments, calculated based on all 683,910 observations in our data set, i.e., including donors as well as those participants who opted out of the donation process without making a contribution. Average donations in the different treatments lie in a range between €1.54 and €1.85 (for more details, see also Table A.1 in the appendix). The confidence intervals marked at the top of each bar indicate that the observed differences across treatments are generally insignificant. If we consider all pairwise treatment comparisons that are possible given our 12 different treatment cells, we find that only 1 out of the 66 pairwise t-tests is significant at the 5% level, and 3 further treatment pairs differ at the 10% level. Specifically, the average donation level in the (10,5) treatment is significantly lower than in the (50,15) treatment, and weakly lower than in the (AD,15) and the (10,15) treatment (t-tests accounting for clustering of standard errors at the session level; p=0.030, p=0.076, and p=0.081, respectively). In addition, contributions in the

[11]For further illustration, Figure B.6 in the online appendix depicts separate donation histograms for individuals who do vs. do not stick to the codonation default. In Section B.1 of the online appendix, we further discuss how people are affected by the specific default tuples in different treatment cells.

(50,15) treatment are marginally higher than in the (AD,5) treatment (p=0.080). The p-values of all other 62 treatment comparisons, however, are well above conventional levels of significance.

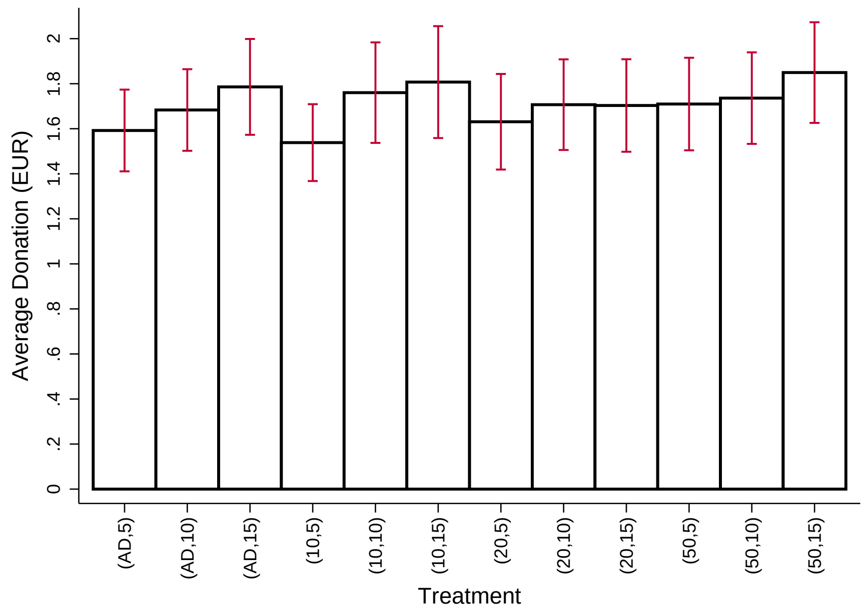


FIGURE 4. Average donation by treatment. *Notes:* The figure depicts average donation levels across the 12 different treatments, calculated based on all participants in the experiment. 95% confidence intervals, accounting for clustering of standard errors at the session level, are presented at the top of each bar.

Most importantly, we observe no systematic influence of different donation defaults on average contribution levels. For instance, average donations under a €10 donation default (bars 4-6 in Figure 4) are very similar to those in the active-decision environment (cp. the three leftmost bars in Figure 4). On average, participants in the AD-treatments contribute €1.69. This compares to €1.70, €1.68, and €1.77 in the treatments with a €10, €20, and €50 donation default, respectively; see Table 5. As is the case for the comparison of individual treatment cells, these differences in average contributions for the "pooled" subsamples are not statistically significant (p>0.3 for all treatment comparisons).[12]

[12]Despite the lack of statistical significance, the relative difference between the observed donation averages might still seem sizable in economic terms (e.g., contributions increase by roughly 5% between the active-decision environment and the €50 default). One has to bear in mind, however, that—our high overall number of observations notwithstanding—small treatment differences in the number of "top donors" with very high contributions can still have a non-negligible impact on the precise values of the average donation levels in a given treatment. For instance, if instead of dropping only the top 0.2% of donors, we would restrict our attention to donors whose contributions do not lie more than three standard deviations above the overall mean across all donors (adopting an approach by Edwards and List 2014), the average donation level in the active-decision environment (€1.45) would actually lie

		Treatment (Donation Default)			
		AD	€10	€20	€50
(1)	Donation rate (%)	3.35	3.39	3.35	3.23
(2)	Av. donation (overall)	1.69	1.70	1.68	1.77
(3)	Av. donation (donors only)	50.29	50.16	50.17	54.59
(4)	Median donation (donors only)	20	20	20	25
(5)	No. Obs.	170,660	170,770	170,977	171,503
(6)	No. donors	5,725	5,795	5,727	5,545

TABLE 5. Summary statistics by default donation level. *Notes:* The table gives an overview of donation behavior for different donation defaults (subsamples pooled across codonation treatments).

Interestingly, some of the bars in Figure 4 seem to suggest that—for a given donation default—average donation levels tend to increase in the *codonation* default. While the effect is relatively modest and generally not statistically significant, it turns significant for one treatment comparison if we pool observations across the different default donation levels (in particular, donations under a 15% codonation default turn out to be significantly higher than under a 5% default (p=0.025) in pooled data).

One might worry that the overall low donation rate in our sample (i.e., the high number of "zero contributions" from platform visitors who end up making no donation) could bias our results towards not finding statistically significant treatment differences at the aggregate level. To address this potential concern, we repeat our analysis with restricted subsamples in which we drop x% of observations for each treatment (all of which involving contributions of zero). One way to interpret this exercise is to assume that x% of participants in our experiment were only browsing the online platform without an inclination to actually make a donation. Doing so for various cutoff levels, e.g., x=10, 25, or 50, we generally find no significant differences in average donation levels across treatments (see Figure B.7 in the online appendix for a more detailed summary of our analysis). In the most extreme scenario, we only keep 3.39% of participants per treatment. This implies that we solely retain the 5,795 actual donors in the €10 treatment (where the donation rate is exactly 3.39%; see Table 5), and no more than 275 non-donors in each of the remaining treatments.

slightly above the value for the €50 treatment (€1.43). Put differently, to conclude that the €50 default systematically increases donations relative to the active-decision environment, one would need to believe that this effect is driven by the default's impact on the fraction (or contribution levels) of participants who donate very high amounts of money. While we cannot conclusively rule out such an effect, it seems implausible.

Nevertheless, we still cannot reject the null hypothesis of no difference in average donation levels at different donation defaults (the lowest p-value for all pairwise treatment comparisons in this case is 0.282). In other words, even at an (implicitly) assumed donation rate in the range of 95-100%, the differences in average donations across treatments are not statistically significant.

Despite the substantial individual-level reactions described in Section 3.1, defaults in our experiment have no systematic impact on average donation levels. Figure 5 explains how both of these findings can be reconciled. In the figure, we show how behavior under a given donation default changes relative to the active-decision environment, and relative to the treatments involving other default specifications. The three frames in the top row of the figure depict the differences in the distributions of donations between the active-decision environment and the €10, €20, and €50 default, respectively. Simply put, we "subtract" the upper-left panel of Figure 3 from the three other histograms depicted in Figure 3, while additionally taking into account potential differences in the proportion of non-donors (i.e., a bar at 0). This allows us to examine how defaults affect the distributions of donations along both the intensive and extensive margin, relative to the active-decision environment. The frames in the second and third row of Figure 5 depict the corresponding pairwise differences in the distributions of donations (and non-donors) for different default donation levels.

If defaults are poles of attraction for people's behavior but there are no significant differences in average donation levels, then it must be the case that defaults induce some people to donate more than they otherwise would have, while others donate less or not at all, such that the two countervailing effects cancel each other out at the aggregate level. This is exactly what we find. Figure 5 demonstrates that, relative to the active-decision environment, people move towards the default from both above and below for each of the different default donation levels.[13] For instance, the spike of additional people donating €20 when this is the default (middle panel in the top row of Figure 5) comes "at the cost" of fewer people donating €5, €10, €25, €50, and €100.

[13]The statistical significance of these movements towards the default is further examined in Section B.2 of the online appendix.

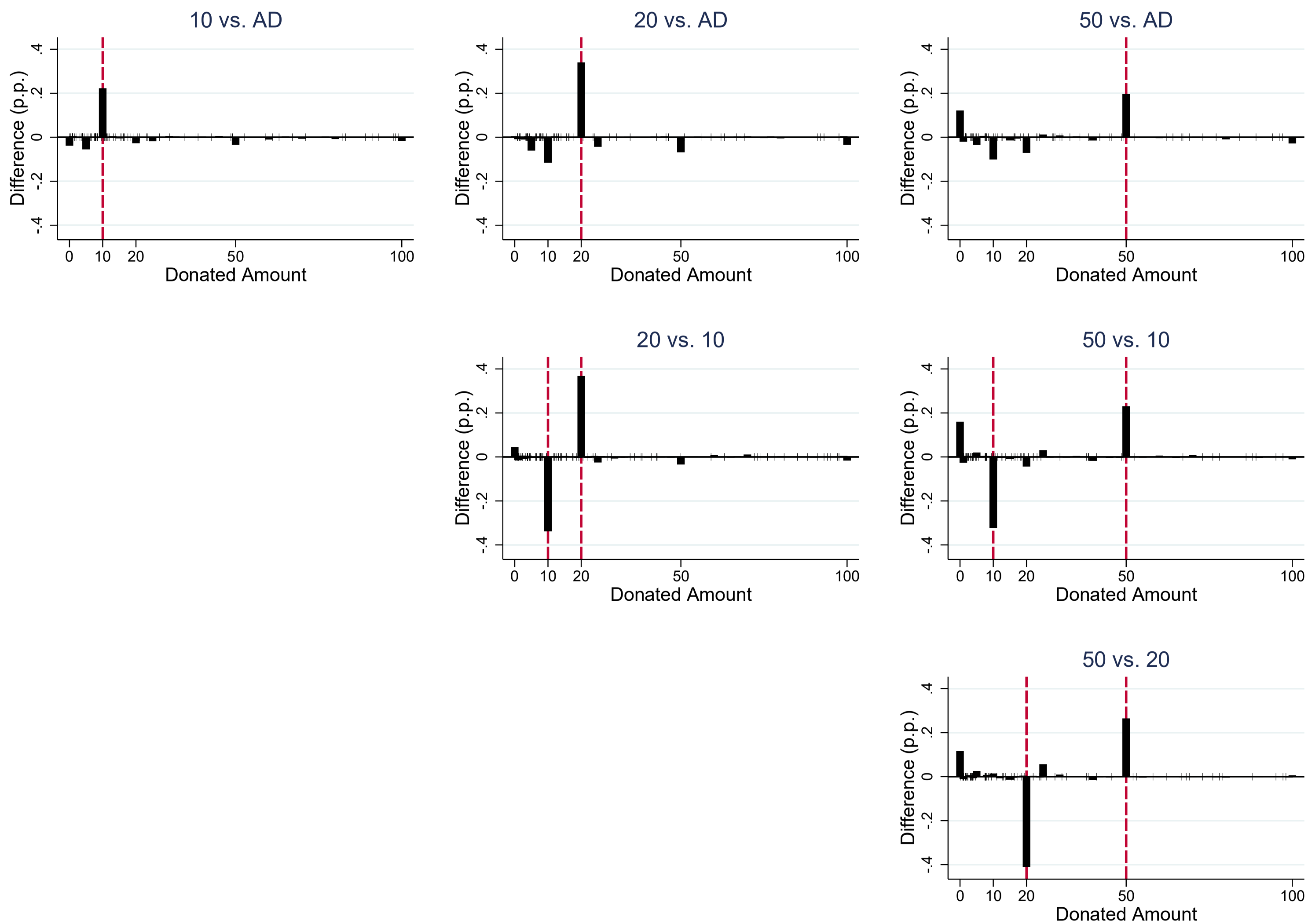


FIGURE 5. Change in donation distributions due to defaults. *Notes:* Each panel of the figure depicts differences (in percentage points) between the distributions of donations under different donation defaults (as indicated in the panel titles). Default donations are indicated by the dashed lines. Extensive-margin differences in the proportion of non-donors are depicted at zero.

Notably, at higher default values, the mass of people who can be "pulled down" by the default becomes smaller and smaller (recall that the €50 default corresponds to the 75th percentile in the distribution of historical donations as well as in the AD treatments). As a result, one might reasonably expect average donation levels to go up. The panels in the right-most column of Figure 5, however, show that there is a second countervailing effect that works against such an increase. In particular, under a €50 default, we observe a higher fraction of participants opting out of the donation process altogether. The donation rate in the treatment with a €50 default is 3.23%. This compares to values of 3.35-3.39% in the remaining treatments (see row 1 of Table 5). Linear-probability models that analyze the propensity of making a donation across treatments show that the drop in the donation rate at the €50 default is statistically significant. The corresponding p-values are p=0.018 when comparing the €50 treatment to all other treatments, and p=0.077 (€50 vs. AD), p=0.022 (€50 vs. €10), and p=0.093 (€50 vs. €20), respectively, for individual treatment comparisons. While the drop in the donation rate might seem modest in size, it suffices to offset the increase in donations at the intensive margin that we observe at the €50 default.[14] As a result, we again observe no significant treatment differences in average donation levels.[15]

In sum, our analysis shows that defaults are important poles of attraction for donors' contribution decisions. We observe strong bunching of donations *exactly at* the respective default in a given treatment, but no systematic changes in the frequency of contributions in the neighborhood of the default amount. Defaults tend to push up the contributions of some donors, even if they do not induce non-donors to become donors. At the same time, they tend to pull others' donations down. At relatively low default values, these two effects seem to operate entirely on the intensive margin. At higher defaults, we find that defaults can also lead to an reduction in donation rates on the extensive margin. In both cases, the countervailing effects essentially cancel each other out,

[14]Focussing only on the subset of participants who do make a donation (row 3 of Table 5), we indeed find a significant increase in the average donation level at the €50 default (p=0.068, p=0.064, and p=0.061 when comparing the €50 treatment to the €10, €20 and AD treatment, respectively).

[15]Interestingly, while this aggregate-level result holds for all of the different donation types, the mechanisms behind the result are somewhat different for the group of participants who come to the platform in response to an organized fundraising event (see Section 2.1). In particular, within this group of participants, we observe no significant drop in the donation rate at the €50 default. Instead, the countervailing effects in this treatment also operate entirely on the intensive margin—i.e., a decrease in the number of donors who give even higher amounts.

leading to small and statistically insignificant average treatment effects for the different donation defaults in our experiment.

3.3. **Do Defaults Affect Average Codonations?** The picture is quite different when considering overall codonation levels. Figure 6 presents average codonation amounts by treatment for our full sample (for further information on codonation levels in the subsample of participants who make positive donations, see Table A.1 in the appendix). The saw-shaped pattern shows that, holding the donation default constant, codonation revenues increase monotonically for higher codonation defaults. The 95% confidence intervals presented at the top of each bar indicate that for most of the relevant pairwise comparisons, these differences are statistically significant. In particular, average codonation levels are always significantly higher at the 15% relative to the 5% codonation default (t-tests accounting for clustering at the session level, p<0.01 in all cases). With the exception of the treatments that involve a €20 donation default, this also holds when comparing the 10% and the 5% codonation treatments (p=0.417 for (20,5) vs. (20,10); p<0.01 in the remaining cases). When comparing the 15% and the 10% codonation treatments, we find that codonations do not differ significantly in the active-decision environment (p=0.458), whereas the differences are significant for the treatments with positive donation defaults (p=0.062, p=0.012, and p=0.001 for the €10, €20, and €50 donation default, respectively).[16]

The magnitude of the observed differences in codonation levels is substantial. For the 15% codonation default, overall codonation levels are roughly 80% higher than under the 5% default and still lie about 30% above the values for the 10% treatments. Comparing the codonation revenues to the overall donation levels in the corresponding treatments underscores this effect. When facing a 5% codonation default, participants on average make an add-on contribution to the online platform that amounts to 2.94% of their donation. This value increases to 3.88% and 4.78%, respectively, under the 10% and 15% codonation defaults. Given that the donation levels themselves are not lowered by higher codonation defaults (see Figure 4), our findings indicate that higher defaults

[16]When comparing average codonation levels under different donation defaults, we find no systematic evidence for a spillover from donation defaults to codonation behavior. In only one case, codonations are significantly higher than in another treatment that features the same codonation default, but a different donation default (specifically, codonations in the (20,5) treatment are higher than in (AD,5) [p=0.048] and weakly higher than in (50,5) [p=0.064]).

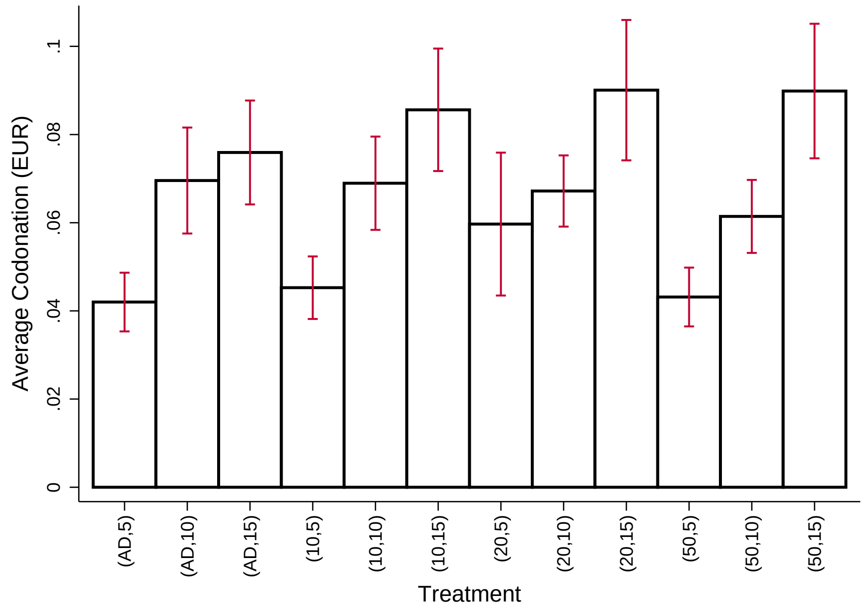


FIGURE 6. Average codonation by treatment. *Notes:* This figure describes average codonation levels across the 12 different treatments. 95% confidence intervals, accounting for clustering of standard errors at the session level, are presented at the top of each bar.

in the codonation dimension increase overall revenues for the online platform without hampering donations to the charitable cause.

Table 4 in Section 3.1 as well as Figure B.5 in the online appendix illustrate how participants' reactions to codonation defaults bring about this positive overall effect. Notably, we find that donors essentially never deviate from a codonation default in order to make a *higher* contribution to the platform. Across all treatments, the fraction of donors doing so is at most 6%. Furthermore, we only observe a modest increase in the proportion of donors who opt out of making a codonation altogether when facing higher default values. The corresponding fraction changes from 42.9% in case of a 5% default to 46.4% and 46.2% for the 10% and 15% default, respectively. While this increase of about 3 percentage points is statistically significant ($p<0.01$ in both cases),[17] it is far from being able to offset the boost in codonations that is caused by the roughly 30-35% of additional donors who make a 10% or 15% codonation when facing these values as a default contribution (see the bold figures in Table 4). This implies that most of the behavioral reactions

[17] These tests are based on linear-probability estimations that compare the propensity of making an add-on contribution for the different codonation defaults, controlling for potential differences across the donation-default treatments. Standard errors are clustered at the session level.

to defaults in the codonation dimension happen on the intensive margin, with movements to the default from below. As a result, we not only observe strong individual-level effects of defaults, but also substantial increases in overall revenues in the codonation dimension.

3.4. **Why Do Defaults Affect Behavior?** A natural question to ask in view of our empirical findings is *why* defaults matter in our setting. Although our experiment is not designed to pin down the precise mechanisms through which defaults affect behavior, our data do permit some informed speculation regarding the psychological mechanisms at work. The literature on default effects has identified numerous mechanisms that may cause people to stick to defaults, such as status-quo biases, attentional limitations, or a tendency to procrastinate (see Dinner et al. 2011 and Sunstein 2013 for comprehensive reviews of the literature). In what follows, we briefly assess the relevance of some frequently discussed candidates in light of our empirical findings. A more detailed discussion of various mechanisms and their predictions for our setting can be found in Online Appendix C.

First, while our data looks *as if* deviating from the default were costly for some agents, it seems highly unlikely that the treatment differences in our experiment can be explained by direct (neoclassical) transaction costs of opting out of the default. For one thing, these costs are essentially zero in online applications, since consumers are in an environment where alternative choices are just “one click away”. For another, the direct costs of altering the donation amount seem negligible in comparison to the other costs that donors incur in order to finalize the transaction, such as filling out the payment details in the donation form.

Second, since we are dealing with an environment where defaults only become relevant in the final stage of a sequence of active choices, explanations based on present-biased preferences and procrastination seem of limited relevance in our setting. Specifically, while a tendency to procrastinate active decision making may contribute to the low overall donation rate that we observe, it seems unlikely that consumers bear the short-run costs of actively going to the platform, selecting a project, etc., but then procrastinate on determining the actual donation amount.

Third, the finding that defaults have no effect on overall donation revenues is inconsistent with a class of psychological mechanisms that predict a monotone increase in average donation levels at higher default values. As we explain in Section C in the online appendix, these mechanisms include explanations based on anchoring as well as simple models of reference-dependent preferences, consumer inattention, or information transmission and recommendations.

More involved variants of these models—e.g., featuring non-linear gain-loss utility or allowing for more general information structures—may be able to rationalize our data. The same holds for some formalizations of the idea that defaults may signal or directly shape prevailing social norms. All of these more involved formulations, however, can rationalize a very wide range of behavioral responses. In this sense, they lack meaningful predictive power.

In sum, none of the predictive mechanism mentioned above is able to account for all of our main empirical findings. Yet, our data suggest that defaults systematically affect people's choices, and that some individuals are systematically more prone to stick to defaults than others. These individuals thus behave as if deviating from the default were costly.[18] In the next section, we will examine this more closely by analyzing whether the platform could make use of the heterogeneity in individuals' reactions to defaults, in order to increase donation revenues.

4. Personalized donation defaults

Our results above show that defaults can be used to increase codonations, but not donations. Defaults in the donation dimension serve as strong attractors, but they make some people donate more than they would otherwise have, and others donate less or not at all. On aggregate, it is a wash. This problem would obviously not arise if the online platform could personalize defaults so that some donations are pushed up but none are pulled down.

In this section we ask whether Betterplace could make use of such a personalization strategy to increase donations revenues. A natural starting point is a reduced-form approach, investigating whether some types of donors are more likely to stick to defaults than others; and whether there are heterogeneous treatment effects in donation levels under different defaults, which might in principle be exploited to target defaults based on trackable individual characteristics. A drawback to this approach is that many personal characteristics of interest are only observable for individuals

[18]A fixed as-if cost of deviating from the default could also rationalize why we observe stronger aggregate-level effects in the codonation dimension in which stakes are smaller and people have a relatively low baseline inclination to contribute (cp. Section 3.3).

who end up making a donation, but not for *potential* donors who visit the website. More generally, the scope for personalizing defaults is limited on (publicly accessible) online fundraising sites since charities—often motivated by privacy and transparency concerns—typically cannot observe, or do not track, potentially relevant individual characteristics. This is in contrast to some “offline” settings (such as alumni fundraising), and it is certainly a limiting factor given the data architecture of Betterplace. In focusing on donor characteristics, our reduced-form approach is therefore bound to ignore responses along the extrinsic margin. That being said, for all realized donations, we can track the calendar time of the donation; whether the donation was towards a fundraising event, a project, or an element within the project; whether the donor was a registered user; and, among registered users, whether a donor has donated on multiple occasions during the observation period, i.e., is a repeat donor. In addition, in the donation form, donors provide their first names, from which we use a name recognition algorithm to deduce their gender.

We explore donors’ propensities to stick to defaults by estimating linear probability models in which the dependent variable is a dummy variable equal to 1 if a donor sticks to a positive donation default or—in an alternative specification—if she sticks to both the donation and the codonation defaults. The estimates (presented in Table B.1 of the online appendix) indicate that donors are not significantly more likely to stick to positive donation defaults in the year-end holiday season (December); donors who contribute as part of a group fundraising event are 2-3 percentage points less likely to stick to the default relative to those who contribute to a particular element or project ($p<0.05$); female donors are 2-3 percentage points more likely to stick to a donation default than males ($p<0.01$); and registered users as well as repeat donors are 1-4 percentage points less likely to stick to donation defaults than their unregistered or non-repeat counterparts, respectively ($p<0.05$ and $p<0.01$). This pattern is qualitatively identical when it comes to sticking to both the donation and codonation defaults, indicating again that some types of donors are generally more likely to stick to defaults than others.

These findings suggest that there may be some scope for personalizing defaults on the basis of gender, donation type and frequency, and user registration. But it doesn’t say much about what that default should be. Heterogeneous responses to different defaults in terms of donation levels are potentially more informative, but our reduced-form results are not very promising in this regard. More specifically, although we observe statistically significant level effects—women, notably, donate €9 less on average than men, and donations are €26 higher in December than at other times of year—none of the interactions between these characteristics and the donation defaults are statistically significant at the 5% level (see Table B.2 in the online appendix).[19]

Our reduced-form results indicate that it may, in principle, be possible to increase donations by targeting defaults based on personal characteristics, but that this strategy requires substantially richer data on donation histories and personal characteristics, not to mention large sample sizes. More generally, personalizing defaults in this manner is unlikely to be a successful strategy given the data constraints on Betterplace and other charitable-giving websites. In the remainder of this section, therefore, we adopt a structural approach that has more modest and arguably more realistic data requirements for the personalization of donation defaults. The model we build requires that the charity can store historical data on individual donations. The thought experiment we wish to conduct is the following. Suppose that the platform can first track individuals' donations in a default-free environment akin to the active-decision treatment (which was the status quo for Betterplace prior to our experiment).[20] This information can be used to recover the donors' underlying "generosity"—how much they are inclined to donate in the absence of a default. The platform can then use this information to personalize defaults, ensuring that they never set a default that is below a donor's baseline generosity level.

To personalize defaults in this manner, one needs to predict how individuals would respond to different default donation levels. The structural exercise below accomplishes this by setting up a model, in Section 4.1, in which donors differ in their generosity levels. They also differ in terms of the "as-if" costs they face when either deviating from the default to a different donation amount, or opting out of donating altogether. Structural estimates of the distributions of donors' underlying

[19]In line with our aggregate-level results for the subset of participants who make a donation (see Table A.1 and Footnote 14), contributions under the €50 default are significantly higher than in the AD treatment in some specifications of Table B.2. This result, however, neglects the extensive-margin reduction in donation rates under the €50 default, illustrating again the limitations of focussing only on the intensive margin of donations.

[20]This kind of tracking is technically feasible in many online settings, by requiring one-step logins upon website entry—e.g., through linked social media accounts—or, as a second-best alternative, using cookies to track IP-addresses.

generosity and as-if costs, described and derived in Sections 4.2 and 4.3, are then used to make out-of-sample predictions of donations under different defaults, which are personalized as a function of a potential donor's underlying generosity, as captured by his or her past contribution in the AD environment. Based on these predictions, we are able to examine, in Section 4.4, whether Betterplace could increase aggregate donation revenues by personalizing defaults.

4.1. **A Simple Model of As-If Costs.** In this section, we study a stylized model to derive a potential donor's optimal contribution in the presence and absence of a default. In so doing, we remain agnostic about individuals' behavioral motivations for adhering to defaults (see Section 3.4 for a discussion of these). Instead, we set up a simple model of "costly opt-out"—in the tradition of Carroll et al. (2009) and Bernheim, Fradkin, and Popov (2015)—in which individuals who deviate from the default incur *as-if* costs that can stem from a variety of possible underlying psychological or economic mechanisms.

In order for this model to be useful, its predictions must match three key empirical features of our data regarding distributional differences under different defaults, summarized at the end of Section 3.2. First, defaults generate bunching at the default but not in its neighborhood, and movements to the default come from both sides of the default. Second, donation rates in the AD environment are not lower than those in the different default treatments: Defaults do not induce non-donors to become donors. Third, high but not low defaults lead to movements along the extensive margin, reducing the donation rate by inducing some potential donors to opt out of the donation process altogether.

Formally, let $x \geq 0$ be the donation made by an individual to the charitable cause. We suppose that there is a stable underlying trait—donor generosity ρ—that determines how much an individual donates in the absence of a default.[21] In the AD environment, without defaults, an individual of type $\rho \geq 0$ maximizes her donation utility $V(x, \rho)$. We suppose that

$$V(x, \rho) = \rho x - \frac{x^2}{2}. \tag{1}$$

[21] In as much as this trait is not stable, we are bound to overestimate the benefits from personalizing defaults based on donors' past donations under an active-decision policy.

This structure enables us to uncover the generosity type ρ from observing the chosen donation x in the AD environment, as the utility-maximizing donation in this case is simply $x = \rho$.

Now consider an agent who faces a default $d > 0$. We suppose that, independent of the default, an ungenerous type ($\rho = 0$) obtains a utility of 0 when opting out of donating altogether. Conversely, a generous type ($\rho > 0$) receives a fixed "opt-out utility" of $-\alpha$ when making no donation (with $\alpha \geq 0$). Intuitively, a generous type may feel bad when donating nothing. An individual who deviates from the default ($x \neq d$) but still donates a positive amount ($x > 0$) incurs a deviation cost $\delta \geq 0$, so that her overall utility is $V(x, \rho) - \delta$.

Note that the above structure allows us to capture the three key features of the empirical donation distributions in the different treatments of our experiment. First, a person donating a positive amount will either stick to the default—thus avoiding the deviation cost δ—or donate an amount equal to her generosity level ρ. This implies that defaults increase the frequency of donations exactly at the default amount from above or below the default, but that donors are not drawn to other positive donation amounts. Second, an ungenerous agent ($\rho = 0$) cannot be induced to give a positive amount. This is in line with our observation that positive defaults do not increase the observed number of donors. Third, defaults may induce donors to opt out of the donation process altogether. This is the case when the fixed cost of doing so (α) is low relative to both the utility $V(\rho, \rho) - \delta$ of giving one's preferred amount, and the utility $V(d, \rho)$ of sticking to the default. This captures the extensive-margin reduction in donation rates at higher defaults.

Simple algebra establishes that the optimal donation $x^o \geq 0$ for a generous agent with $\rho > 0$ in the presence of a default option $d > 0$ is given by

$$x^o = \begin{cases} d & \text{if } V(d,\rho) > V(\rho,\rho) - \delta \text{ and } V(d,\rho) \geq -\alpha \\ \rho & \text{if } V(\rho,\rho) - \delta \geq V(d,\rho) \text{ and } V(\rho,\rho) - \delta \geq -\alpha \\ 0 & \text{if } \max\{V(\rho,\rho) - \delta, V(d,\rho)\} < -\alpha \end{cases} \tag{2}$$

To simplify notation, let

$$\Delta(\rho, d) \equiv V(\rho, \rho) - V(d, \rho) = \frac{\rho^2 + d^2}{2} - \rho d.$$

We assume that there is a share λ_1 of agents who act as if deviating from the default is costless. These agents experience no deviation costs δ and therefore always donate their preferred amount ρ.[22] The remaining $1 - \lambda_1$ share of agents has positive deviation costs. The optimal donation decision of agents who face deviation costs will depend on their generosity level. For relatively generous agents, it is never optimal to opt out of making a donation altogether. Specifically, for agents with a generosity level $\rho \geq d/2$, sticking to the default yields utility $\rho d - d^2/2 \geq 0$, whereas the utility from opting out and making no donation is $-\alpha < 0$. These relatively generous agents will therefore either stick to the default or donate their preferred amount ρ, depending on whether their deviation costs δ are larger or smaller than $\Delta(\rho, d)$. Agents with relatively low generosity, $0 < \rho < d/2$, also determine their choice of sticking to the default or deviating to their preferred amount depending on which side of the cutoff, $\Delta(\rho, d)$, their δ lies. For low-generosity agents, however, the utility of donating d and the utility of deviating to ρ may both be smaller than the opt-out utility $-\alpha$. When this is the case, it is optimal for low-generosity agents to opt out of donating altogether. Finally, ungenerous agents with $\rho = 0$ will never make a positive donation.

4.2. **Estimation.** There are three unknown parameters in this model: generosity types ρ, deviation costs δ, and opt-out costs α. A key advantage of our data is that we can identify the distribution function $f(\rho)$ non-parametrically from the observed donation distribution in the AD treatment, which features no default and therefore entails no deviation costs.

Modeling costs requires more structure, since costs are not directly observed. In keeping with Bernheim, Fradkin, and Popov (2015), we allow for heterogeneous deviation costs that follow an exponential distribution. Specifically, we assume that conditional on belonging to the share $1 - \lambda_1$ of agents that have positive deviation costs (whom we index by $z = 1$), the cost δ of deviating from the default to a positive donation amount is distributed according to the cumulative distribution function Φ, where

$$\Phi(\delta | z = 1) = \begin{cases} (1 - e^{-\lambda_2 \delta}), & \text{for } \delta \geq 0, \\ 0, & \text{for } \delta < 0. \end{cases}$$

[22]Note that these agents might still be subject to opt-out costs (α), but the latter are irrelevant for agents' choices. This is because agents can costlessly deviate from the default to their preferred donation amount ρ, which guarantees strictly positive utility.

Once again following Bernheim, Fradkin, and Popov, we further assume that ρ and δ are independently distributed. As for the costs of opting out of the donation process altogether, we assume that making no donation entails no costs for ungenerous types ($\alpha = 0$ for agents with $\rho = 0$). For generous types ($\rho > 0$), the opt-out cost α is distributed according to the cumulative distribution function Ω, where

$$\Omega(\alpha|\rho > 0) = \begin{cases} (1 - e^{-\lambda_3 \alpha}), & \text{for } \alpha \geq 0, \\ 0, & \text{for } \alpha < 0, \end{cases}$$

and is distributed independently of δ and ρ.

Given that $f(\cdot)$ is already non-parametrically identified from the AD treatment, the estimation problem boils down to identifying the three parameters of the model that define the cost distributions—a proportion λ_1 which is inure to deviation costs; and the parameters of the exponential distributions λ_2 and λ_3, which define the deviation costs and opt-out costs, respectively. We estimate these parameters by maximizing a log-likelihood function of the following form:

$$L(\lambda) = \sum_{i=1}^{N} \log(\Pr(x_i|d, \lambda, f(\cdot)))$$

where $i = 1, ..., N$ are the individual observations in the treatments with positive donation defaults. Section D.1 in the online appendix provides a detailed derivation of the log-likelihood function. In essence, the likelihood function in our setting consists of the different cases involved in the optimal donation decision described in Equation (2), weighted by the corresponding probabilities with which they occur, given the (estimated) parameters of the model. For example, the probability of observing an individual donating €15 in a treatment with a €50 default depends on the prevalence of individuals with a generosity type $\rho = 15$, the fraction of individuals that are subject to deviation costs $(1 - \lambda_1)$, as well as the distributions of the deviation and opt-out costs (determined by λ_2 and λ_3).

Note that the log-likelihood function is only defined if $f(\rho)$ takes on positive values for all ρ. As the empirically observed donations in the AD treatment take discrete values and the data becomes sparse at donations above €300, we restrict the sample in our estimation to $\rho \in [0, 300]$ and "smooth" our data by assigning donations to integer bins, such that each bin has positive mass. The observations used in the estimation amount to 99.9% of the total sample. Parameters $\lambda = (\lambda_1, \lambda_2, \lambda_3)$ are identified through changes in the donation distribution under the different donation defaults in our experiment, relative to the AD treatment (cp. Figure 5).

4.3. **Estimation Results.** Maximum likelihood estimates for λ are presented in Table A.2 of the appendix. The estimate for λ_1 indicates that 89% of potential donors are inure to, or simply ignore the default. This proportion, though seemingly high, is entirely in line with the empirically observed responses to defaults in our experiment. In particular, recall that the proportion of donors who contribute the default amount under different donation defaults increased by roughly 5-10 percentage points relative to the AD environment (cp. Table 3). Default options thus substantially affect the behavior of *some* individuals, but they leave a majority of potential donors untouched.[23]

Among the 11% of potential donors who do incur costs, the estimates for λ_2 and λ_3 indicate that deviation costs and opt-out costs are rather high.[24] High deviation costs imply that agents who are subject to these costs are inclined to stick to the default, generating modes in the distributions of donations at the corresponding default values. At the same time, the estimate for λ_3 is larger than the estimate for λ_2, indicating that opt-out costs tend to be smaller than deviation costs. The upshot of this is that opting out of donating altogether may be preferable to donating a non-default amount, especially for potential donors who are less generous. At high enough defaults, this generates movements along the extensive margin.

The model with these parameter estimates performs remarkably well. As Figure 7 shows, the fitted model successfully reproduces all of the key features of the data from our experiment: it generates the empirically observed modes at the €10, €20, and €50 defaults, reproduces the

[23]This finding might seem surprising in light of the evidence that defaults affect a large share of the population in applications like retirement savings or organ-donor registration. Note, however, that some of the potential mechanisms behind default effects in these settings are, by design, less relevant in ours (such as hassle costs of opting out or present-biased procrastination; cp. Section 3.4). Hence, our relatively high estimate for λ_1 may indicate that procrastination *is* indeed a major driver of default effects in those other settings.

[24]These costs are measured in utils and are therefore not directly interpretable in monetary terms. Figure D.1 in the online appendix, however, gives a sense of what "high" means in this context by plotting the $\Delta(\rho, d)$ functions under the three different defaults, as well as the mean and median of δ implied by our estimates. The figure shows that for agents of type $\rho \leq$ €158 (168) [198], the median deviation costs are high enough to make the agents stick to a default of €10 (€20) [€50], rather than donating their preferred amount ρ.

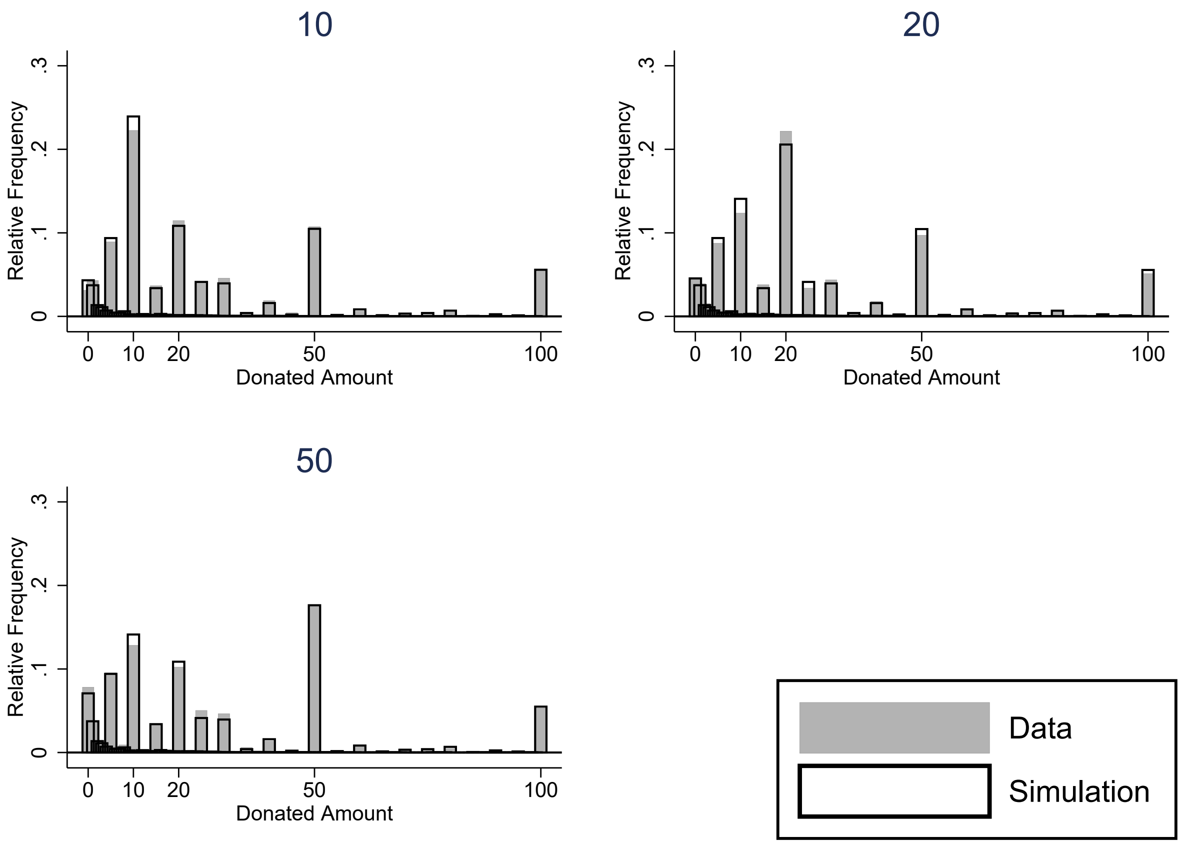
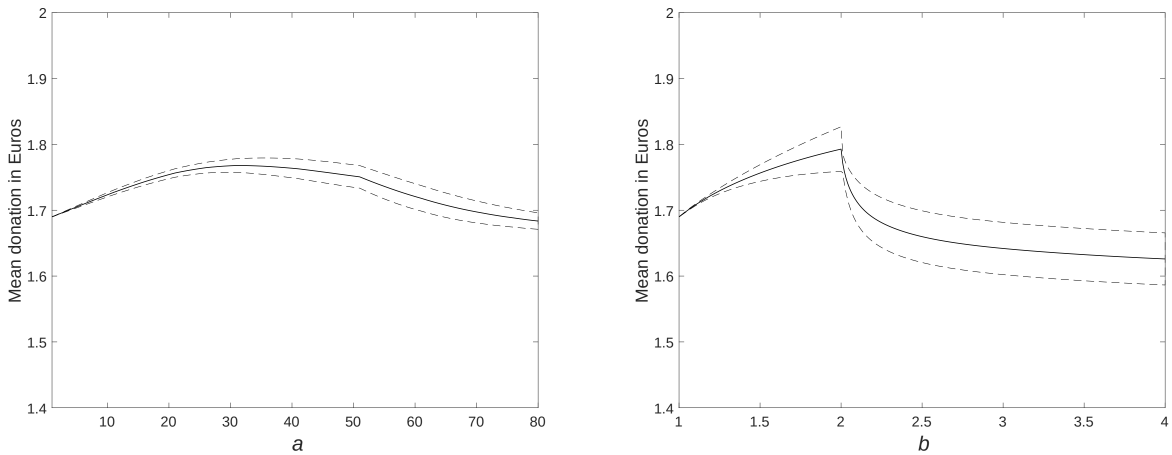


FIGURE 7. Fitted versus Actual Donation Distribution. *Notes:* The figure compares the empirically observed distributions of donations in the experiment to (simulated) fitted distributions, using the non-parametric distribution $f(\cdot)$ from the AD treatment for integer values of ρ and the maximum likelihood estimates of λ from Table A.2 in the appendix. For the simulated ρ's, a random sample of the distribution function $f(\rho)$ is drawn with N=500,000. For illustrative reasons (i.e., to avoid extreme spikes at 0 due to the high share of non-donors), the analysis focuses on a subsample containing 3.5% of the overall sample in each treatment (all actual donations and the corresponding number of zero contributions per treatment), excluding donations above 300.

decrease in the donation rate (i.e., the spike at zero) under the €50 default, and closely matches the empirical distributions elsewhere.

4.4. **Personalized Defaults.** Using the parameter estimates for λ, we can now make out-of-sample predictions regarding how donation revenues would change under a system of personalized defaults. Specifically, we examine how the platform could optimally condition defaults on an individual's (past) donation level in the absence of defaults, captured in our model by the parameter ρ. As is immediately clear from our derivations above—as well as from the empirical observation that defaults pull some donors' contributions down relative to the AD treatment—it never makes sense to set the donation default for a given individual below his or her generosity type ρ. We therefore simulate two types of personalized defaults. The first is additive: an individual of type ρ is assigned a default of $\rho + a$, where $a \geq 0$. The second is proportional: an individual of type ρ is assigned a default of $\rho \cdot b$, where $b \geq 1$.



(A) Additive: $d(\rho) = \rho + a$ (B) Proportional: $d(\rho) = \rho \cdot b$

FIGURE 8. Donations under Personalized Defaults *Notes:* This figure plots means and confidence intervals of donations under different personalized default-setting policies, based on simulated data. Personalized defaults are determined by adding a constant a to the agent's baseline generosity level ρ (left panel) or multiplying it with a a factor b (right panel). Agents' response to the personalized default is simulated for a range of different values of a and b. The confidence interval accounts for uncertainty in the estimated parameters. We re-estimate the λ parameters with bootstrap samples from the €10,20, and 50 default treatments and replicate this a 1000 times. For each of these estimated λ parameters, we simulate the agents' response to the personalized defaults and construct a confidence interval around these means. The simulations are carried out with a large sample of ρ's drawn from the AD treatment to approximate well the distributions of the as-if costs.

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Figure 8 furnishes our model's predictions of mean donation levels under personalized defaults for the additive (Panel A) and proportional case (Panel B). Under the additive default option, donations are maximized at $a^* = 31.3$. The optimal scaling factor for the proportional personalized default is $b^* = 2.0$.[25] Under these defaults, our model predicts that overall donation revenues

[25]The optimal add-on and scaling factor may seem high, but they follow naturally from our parameter estimates in the previous section, our model specification, and the empirical results from Section 3: since a majority of potential donors is generally inure to defaults, it doesn't matter for them when this default if high. For the rest, a high personalized default may lead some to completely opt out of the donation process, but those that don't are induced to contribute a

would increase by at most 6.2% relative to the AD environment (4.7% in the additive and 6.2% in the proportional case). While this increase in donation revenues seems economically relevant, we think of it as an upper bound for the potential gains to be made from personalization in our setting. Specifically, if the donors' generosity level fluctuates over time or varies by project, the gains from personalized defaults are bound to be lower. Moreover, our simple functional form of individuals' donation utility $V(\cdot)$ implies that increasing an potential donor's default to up to twice her preferred amount does not trigger an extensive-margin reaction. The fact that we see a sharp drop in predicted revenues for proportional scaling factors above 2 suggests that individuals may drop out somewhat earlier if we allowed for a more flexible specification of their preferences. Hence, despite our model's ability to replicate key data patterns of our experiment, the potential benefits of personalizing defaults in our setting seem rather limited.

5. Conclusion

We conclude by discussing practical implications of our findings for charitable organizations and providers of online donation platforms. Most importantly, our results highlight the possibility that defaults may have both desired and undesired effects on the distribution of donations and overall donation revenues. They also demonstrate that defaults may have an influence on people's decisions, even if this influence might not be directly apparent in aggregate-level data.

Both observations caution against a simplistic use of defaults based on the notion that "defaults work". This, of course, does not to imply that positive defaults may never increase donation revenues. The use of personalized or adaptive defaults seems promising in this respect, but our results from Section 4 suggest that it is challenging to successfully increase donations through personalized defaults in a setting like ours. While our reduced-form results indicate heterogeneity across groups in terms of potential donors' proclivity to stick to defaults as well as in the overall propensity to contribute, we find no compelling evidence of heterogeneous donation responses to defaults. The results from our structural estimates are not much more encouraging. They indicate

higher amount. Optimal personalized defaults are those that best manage the tradeoff between driving some people out and others up. This can be readily seen in the case of proportional personalization. The scaling factor of 2 implies that nobody is induced to opt out entirely under their personalized default, since individuals with $\rho \geq d/2$ always stay in the donation process (see Section 4.1). At the same time, individuals with high deviation costs δ will stick to the default, thereby generating higher revenues for the charity.

that personalized defaults have the potential to avert downward movements in donations by setting defaults neither too high nor too low for a given donor, but they also suggest that successful personalization requires much richer data. While the data constraints that limit our analysis in this respect are, at present, shared by many other online charitable giving platforms, better tracking of data from donors and their reactions to different features of the platforms—as well as linked data from other sources—might eventually make such an approach feasible.

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APPENDIX

		Treatment (D€, C%)												
		(AD,5)	(AD,10)	(AD,15)	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)	F-Stats
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
		Donations												
(1)	Donation rate (%)	3.34	3.27	3.45	3.35	3.45	3.38	3.31	3.39	3.35	3.14	3.35	3.21	
(2)	Av. donation (overall)	1.59	1.68	1.79	1.54	1.76	1.81	1.63	1.71	1.70	1.71	1.74	1.85	
(3)	Av. donation (donors only)	47.65	51.44	51.76	45.90	51.10	53.44	49.31	50.33	50.85	54.53	51.82	57.54	
(4)	Median donation (donors only)	20	20	20	20	20	20	20	20	20	23	25	25	
		Codonations												
(5)	Conation rate (%, all)	1.82	1.70	1.77	1.94	1.89	1.90	1.94	1.93	1.85	1.80	1.69	1.69	
(6)	Conation rate (%, donors only)	54.50	52.04	51.43	57.91	54.89	56.12	58.68	56.77	55.25	57.39	50.55	52.52	
(7)	Av. codonation (€, all)	0.042	0.070	0.076	0.045	0.069	0.086	0.060	0.067	0.090	0.043	0.061	0.090	
(8)	Av. codonation (€, donors only)	1.26	2.13	2.20	1.35	2.00	2.53	1.80	1.98	2.69	1.38	1.83	2.80	
		Project Background Characteristics												
(9)	Fundraising Event	0.118	0.116	0.117	0.118	0.116	0.116	0.115	0.116	0.117	0.114	0.117	0.118	0.658
(10)	Project	0.339	0.339	0.338	0.338	0.338	0.338	0.340	0.340	0.336	0.337	0.339	0.336	0.827
(11)	Element	0.542	0.544	0.545	0.544	0.545	0.546	0.545	0.543	0.548	0.549	0.544	0.546	0.620
(12)	Tax Deductible	0.661	0.657	0.655	0.659	0.660	0.658	0.660	0.655	0.660	0.658	0.657	0.656	0.317
(13)	N. Obs.	56,894	56,959	56,807	56,739	57,014	57,017	56,777	57,083	57,117	57,138	56,985	57,335	
(14)	N. donors	1,901	1,864	1,960	1,903	1,964	1,928	1,878	1,936	1,913	1,793	1,909	1,843	

TABLE A.1. Summary Statistics. *Notes:* The top and middle panel provide an overview of key outcome variables in the different treatments. The bottom panel provides an overview of observed project background characteristics. Rows (9)–(11) report the proportion of observations in a given treatment which pertain to a fundraising event (e.g., a birthday or charity run), an aid project, or a specific element within a project (e.g., a first aid kit within a Red Cross Project), respectively. Row (12) pertains to the proportion of observations per treatment group which were eligible for a tax deduction (typically the case when the charity is registered in Germany). The final column reports p-values from F-tests for treatment differences in background characteristics, based on separate regressions of each of the characteristics on dummies for the different treatments.

Parameter	Estimate	Standard error
λ_1	$89.0{\times}10^{-2}$	$43.1{\times}10^{-4}$
λ_2	$62.8{\times}10^{-6}$	$34.4{\times}10^{-6}$
λ_3	$99.1{\times}10^{-5}$	$30.2{\times}10^{-5}$

TABLE A.2. Parameter Estimates. *Notes:* Results obtained from maximum likelihood estimation. Standard errors are computed numerically by using a variant of the Berndt et al. (1974) algorithm to approximate the Hessian. Estimation are based on all observations with $\rho \in [0, 300]$, which accounts for 99.92% of the overall sample.

Online Supplementary Material For:

Defaults and Donations: Evidence from a Field Experiment*

Steffen Altmann, Armin Falk, Paul Heidhues, Rajshri Jayaraman and Marrit Teirlinck

July 2018

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Online Appendix B: Additional Results

FIGURE B.1. Translation of Figure 1.

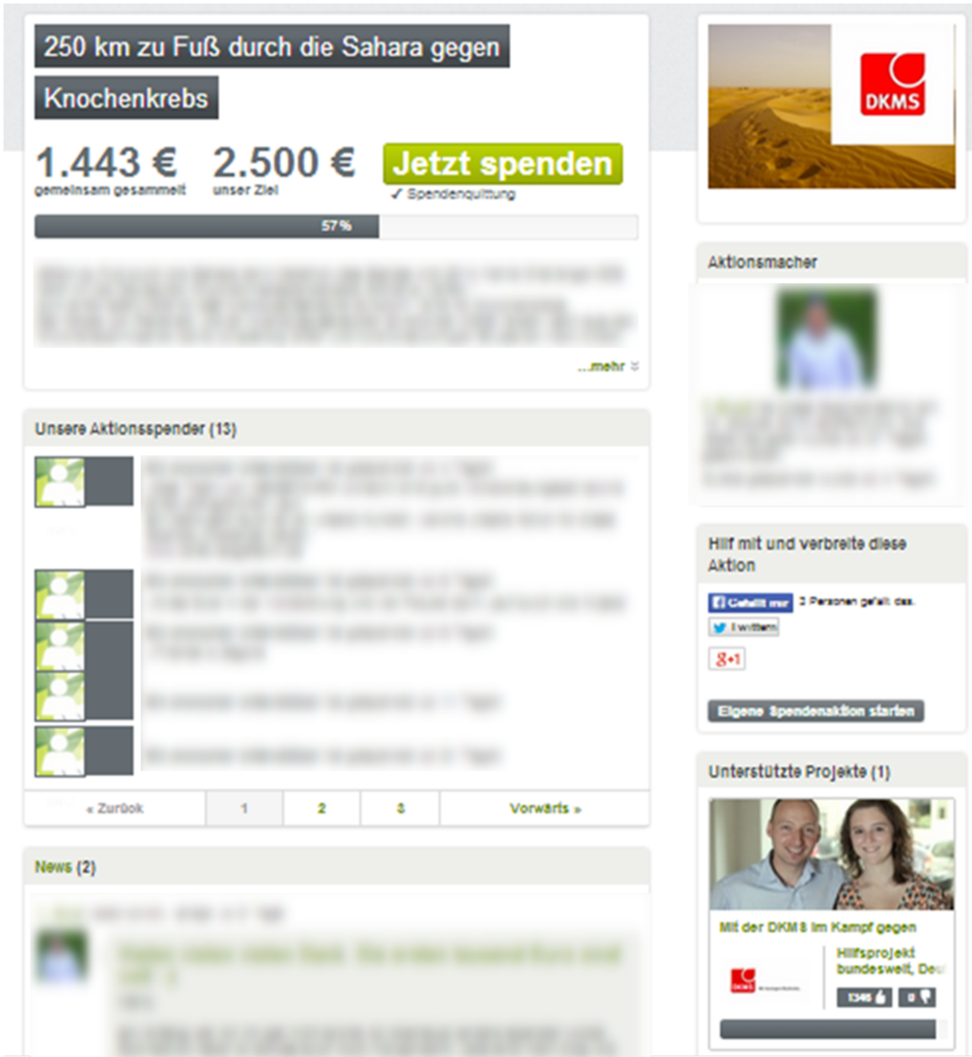

FIGURE B.2. Page of a fundraising event. *Notes:* The example displays a 7-day charity run through the Sahara (described in more detail at the top of the page) in support of an aid project by the German unit of "Delete Blood Cancer" (described and linked at the bottom right part of the page).

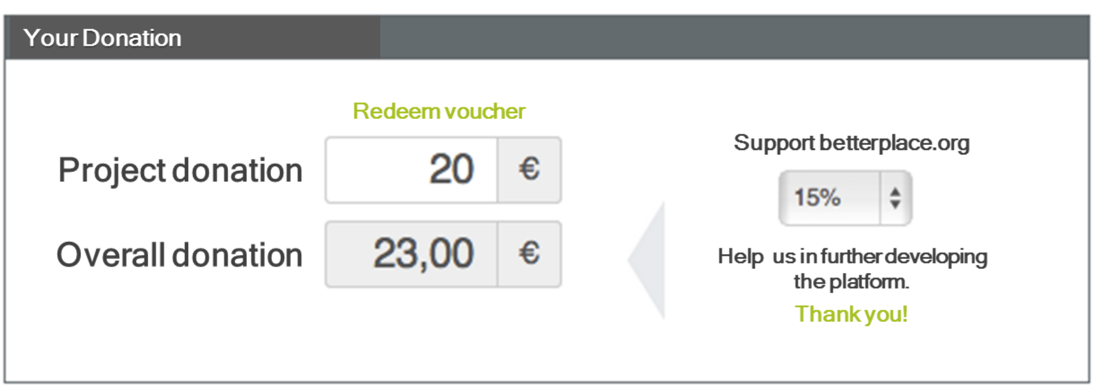

FIGURE B.3. Translation of Figure 2.

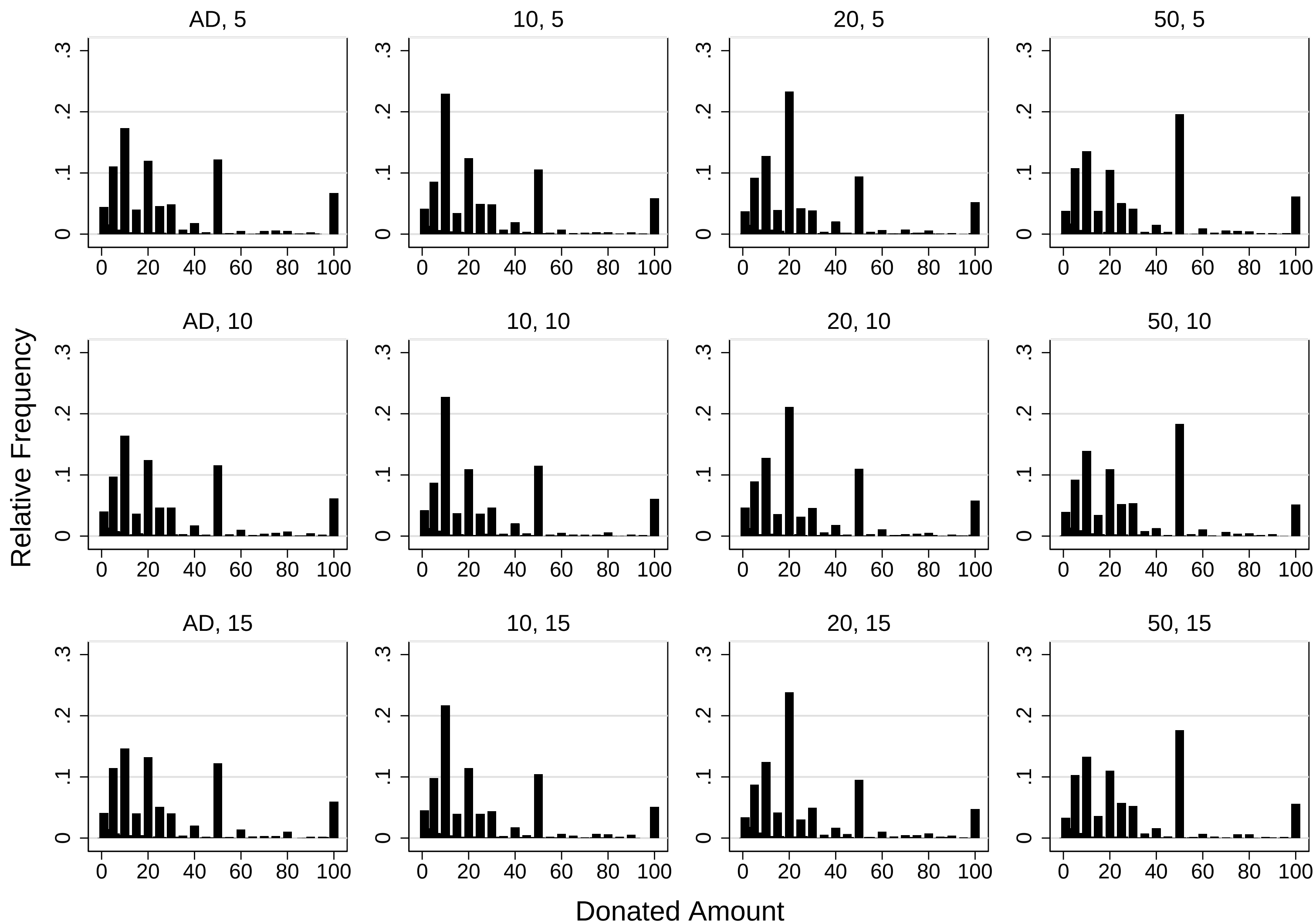

FIGURE B.4. Donation distributions by treatment. *Notes:* This figure describes the relative frequencies of donations in the different treatments, denoted by their respective donation / codonation default.

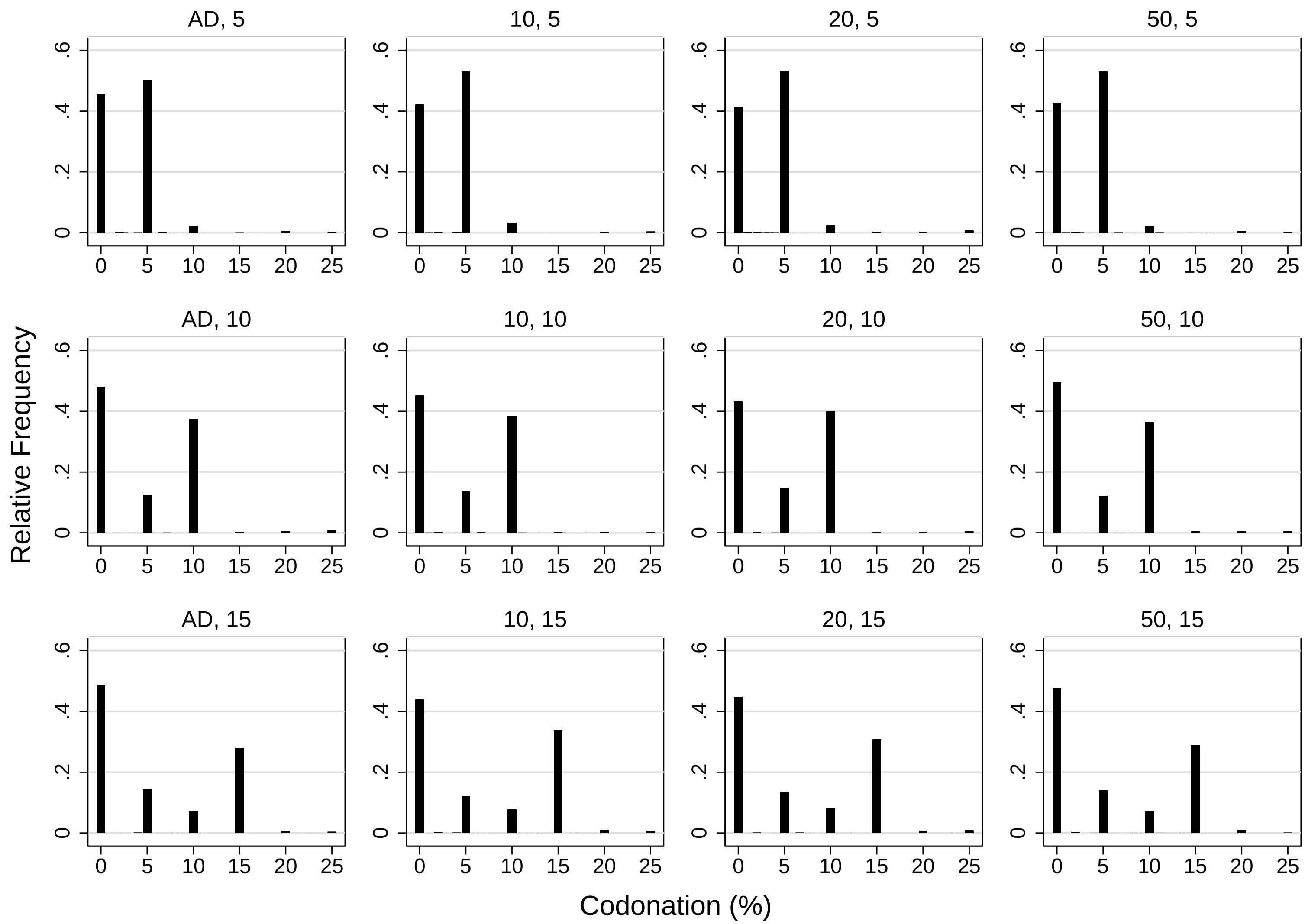

FIGURE B.5. Codonation distributions by treatment. *Notes:* This figure describes the relative frequencies of codonations in the different treatments, denoted by their respective donation / codonation default.

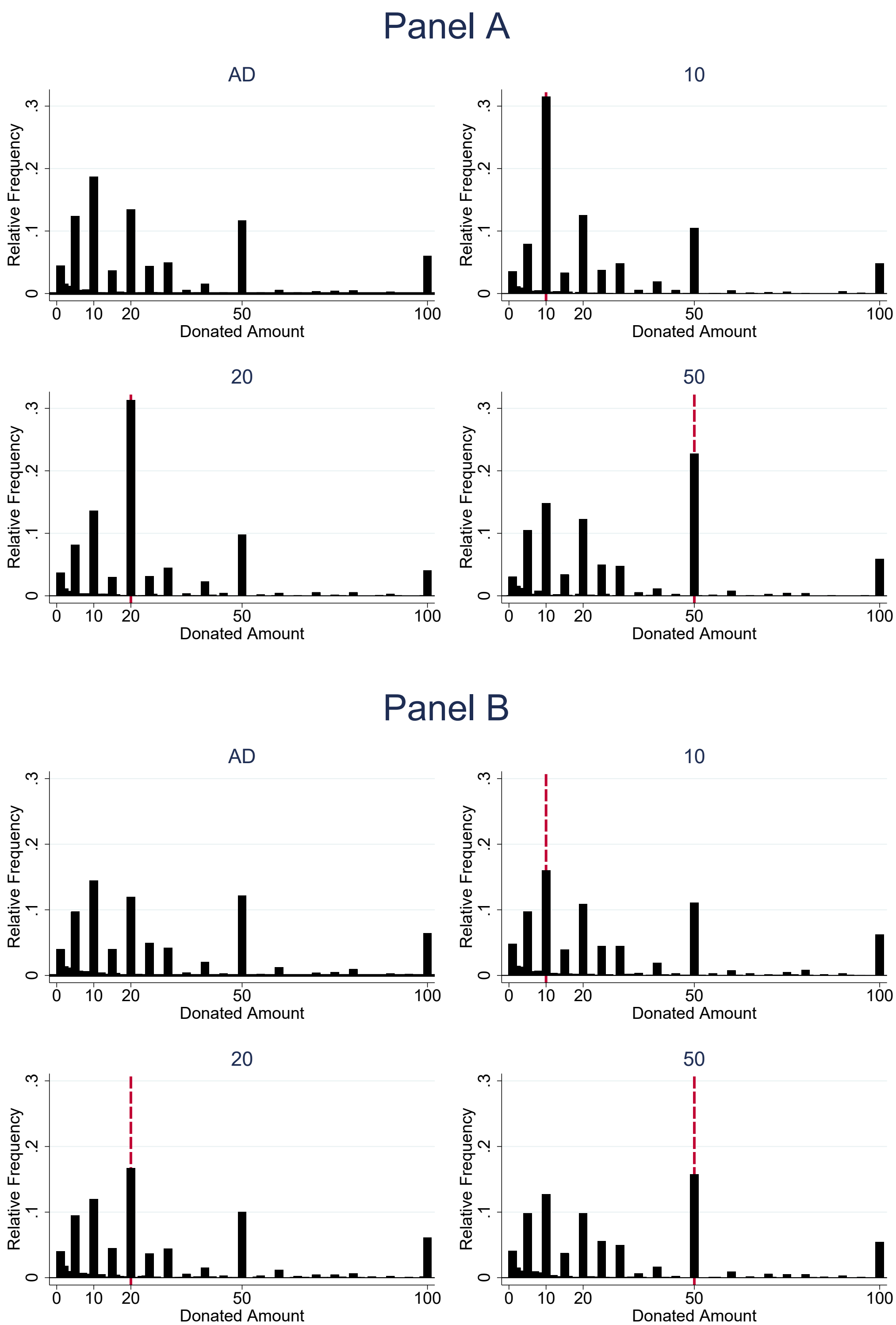

FIGURE B.6. Distributions of donations. *Notes:* This figure depicts the relative frequencies of donations in different treatments, separately for individuals who stick (Panel A) vs. opt out (Panel B) of the default in the codonation dimension.

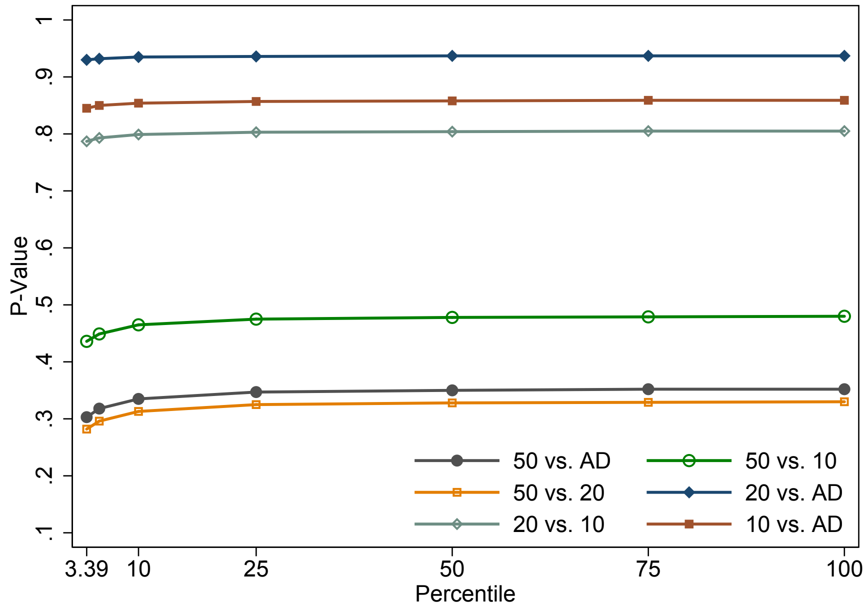

FIGURE B.7. Treatment differences in donation levels. *Notes:* The figure depicts p-values from t-tests comparing donation levels for different default values. Each line pertains to a different two-way t-test with the null hypothesis that there is no difference in average donations at two different donation defaults (i.e., €50 vs. €20; €50 vs. €10; €50 vs. AD; €20 vs. €10; €20 vs. AD; and €10 vs. AD; pooling across different codonation default in each case). Tests are based on subsamples containing the X% of observations with the highest contribution levels in a given treatment (i.e., all actual donors and the corresponding number of zero contributions). For instance, the left-most tick on the x-axis corresponds to tests based on a subsample that contains the top 3.39 percent of contributions in a given treatment, the second [third] tick includes additional non-donors up to the 5th [10th] percentile in a given treatment, etc. The right-most tick presents p-values from tests that are based on the full sample considered in Section 3 of the paper.

	Stick to Donation Default			Stick to Both Defaults		
	(1)	(2)	(3)	(4)	(5)	(6)
Year End	-0.002	-0.002	0.002	-0.002	-0.002	0.002
	(0.006)	(0.007)	(0.011)	(0.005)	(0.005)	(0.007)
Fundraising Event	-0.033***	-0.026***	-0.024**	-0.017***	-0.012**	-0.006
	(0.007)	(0.007)	(0.011)	(0.005)	(0.006)	(0.008)
Project	-0.001	0.001	0.006	-0.003	-0.002	0.004
	(0.007)	(0.007)	(0.010)	(0.005)	(0.005)	(0.007)
Female		0.033***	0.024***		0.028***	0.028***
		(0.005)	(0.008)		(0.004)	(0.006)
Repeat Donor			-0.044***			-0.046***
			(0.008)			(0.006)
Registered User	-0.016***	-0.012**		-0.021***	-0.017***	
	(0.005)	(0.005)		(0.004)	(0.004)	
Constant	0.020***	-0.001	0.013	0.017***	-0.001	0.009
	(0.006)	(0.007)	(0.010)	(0.004)	(0.005)	(0.007)
Treatment Dummies	YES	YES	YES	YES	YES	YES
Observations	22,792	21,120	9,080	22,792	21,120	9,080
R-squared	0.068	0.071	0.069	0.041	0.045	0.046

TABLE B.1. Propensity to Stick to Defaults. *Notes:* This table contains estimation results from linear probability models in which the dependent variable is a dummy variable equal to 1 if the donor sticks to the donation default [Columns (1)–(3)], and equal to 1 if the donor sticks to both the donation and codonation defaults [columns (4)–(6)]. "Year End" is a dummy variable equal to 1 in December 2012—the holiday season; "Fundraising Event" and "Project" are dummy variables equal to 1 if the donation was towards a fundraising event or a project, respectively (the omitted category are project elements); "Female", and "Registered User" are dummy variables defined accordingly. "Repeat Donor" is a dummy variable equal to 1 if a participant donated repeatedly (information only available for registered users). Each regression includes a vector of 11 dummy variables controlling for treatment assignment. Standard errors are clustered at the session level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Characteristic	Female	Repeat Donor	Registered User	Year End
	(1)	(2)	(3)	(4)
€10 Default	2.583	0.794	-1.291	-0.326
	(3.479)	(4.715)	(3.024)	(2.288)
€20 Default	0.462	2.306	-3.590	0.591
	(3.352)	(4.927)	(2.827)	(2.196)
€50 Default	7.218**	3.673	1.893	5.661**
	(3.480)	(4.648)	(2.947)	(2.278)
Characteristic	-9.126***	2.683	-2.768	25.931***
	(2.914)	(4.733)	(3.054)	(4.951)
€10 Default × Characteristic	-6.881*	1.256	2.799	1.173
	(4.173)	(6.950)	(4.605)	(7.071)
€20 Default × Characteristic	-2.001	4.000	8.036*	-3.041
	(4.264)	(7.143)	(4.556)	(7.143)
€50 Default × Characteristic	-6.149	7.509	5.696	-5.429
	(4.386)	(7.133)	(4.620)	(7.258)
Constant	53.020***	47.372***	51.440***	44.923***
	(2.230)	(3.583)	(1.952)	(1.457)
Observations	21,120	9,810	22,792	22,792
R-squared	0.004	0.001	0.000	0.007

TABLE B.2. Heterogeneous Treatment Effects of Default Donations on Donations. *Notes:* This table contains OLS regression output in which the dependent variable is the donated amount, for donors. The "Characteristic" in the respective columns are dummy variables equal to 1 if, as indicated in the column headings, the donor (1) is female; (2) has donated more than once over the observation period (only available for registered users); (3) is a registered user; and (4) donated in December 2012—the holiday season. Treatment-level effects are captured by the dummy variables in rows 1-3; row 4 captures the respective characteristic's level effect; rows 5-7 capture heterogeneous treatment effects (the corresponding treatment dummy times the respective characteristic.) The exclusion is the AD treatment. Standard errors are clustered at the session level. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

B.1. **Default Adherence in Both Treatment Dimensions.** In this section, we illustrate in more detail how the combination of defaults in both treatment dimensions affects the joint distribution of donations and codonations. Table B.3 depicts the number of donors across treatments who choose donation-codonation tuples along a grid that is defined by the different combinations of donation-codonation defaults in our experiment. The table thus combines the evidence depicted in Tables 3 and 4, restricting the "action set" to the grid imposed by the 9 different default combinations from our treatments. The highlighted cells in Table B.3 demonstrate that the modal action in this partial distribution invariably corresponds to the default amounts for each of our treatments, mirroring the observations from the separate choice dimensions (Tables 3 and 4) for the joint distribution.

The mass of observations at the defaults observed in Table B.3 is clearly non-random. To see this, consider the null hypothesis that defaults are not a pole of attraction for people's behavior, and consider the first row of Table B.3. This row looks at the number of donors who choose to donate $(10, 5)$ for each of the 12 treatments. Absent default effects, any cell in this row is equally likely to contain the highest frequency of donors. Hence, the probability that we observe the highest frequency of donors contributing $(10, 5)$ in treatment $(10, 5)$ when there is no default effect is $1/12$. Similarly, in any other row the probability that the highest frequency of donors falls into the cell in which this choice happens to be the default option is $1/12$. One may thus be tempted to conclude that the probability that the highest frequency of donors always choose a given action in the treatment where this action happens to be the default is $(1/12)^9$, which however ignores that these tests are not independent. To see this, suppose that the highest frequency of donors choosing the action $(10, 5), (10, 10), (10, 15), ..., (50, 5), (50, 10)$ would fall into the treatment $(10, 5)$ (and no donor chooses an amount not on the grid). Then, the highest frequency of donors for the action $(50, 15)$ cannot fall into the treatment $(10, 5)$ as the numbers cannot exceed 100%. A very conservative estimate is to assume that in case the highest frequency of donors gives the default amount in the first treatment, this treatment cannot have the highest amount of donors in any other treatment, and similarly for any subsequent treatment. For this conservative estimate, the chance that the default amount has the highest frequency of donors is bounded from above by $1/\,(12 \times 11 \times \ldots \times 4) = 1/79,833,600$.

	Treatment (d€, c%)											
	(10,5)	(10,10)	(10,15)	(20,5)	(20,10)	(20,15)	(50,5)	(50,10)	(50,15)	(AD,5)	(AD,10)	(AD,15)
Action	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(10,5)	**290**	39	33	133	29	24	128	32	30	166	36	36
(10,10)	14	**258**	23	10	102	24	7	108	20	9	146	18
(10,15)	0	1	**211**	1	1	85	0	0	87	2	1	97
(20,5)	132	39	24	**295**	47	59	124	24	44	123	28	44
(20,10)	16	90	19	6	**234**	35	3	87	17	7	92	30
(20,15)	0	0	81	2	0	**210**	0	1	56	0	0	78
(50,5)	122	52	38	100	42	33	**224**	35	35	128	39	40
(50,10)	2	73	17	9	86	14	9	**154**	25	0	74	18
(50,15)	0	0	56	0	0	46	0	1	**117**	0	0	54

TABLE B.3. Number of donations and codonations at default amounts. *Notes:* The table denotes the number of observations which correspond exactly to the donation and codonation default amounts of the different treatments.

B.2. **Movements Towards the Donation Default.** In Table B.4, we examine the statistical significance of the observed movements towards the different donation defaults relative to the active-decision environment (Figure 5 in the paper). In each row of the table, we estimate different models that compare the relative frequencies in contributions between one of the donation-default regimes and the active-decision environment. Column 1 denotes the treatment that we consider in a given row. Column 2 depicts the increase in the fraction of donations at the corresponding default amount, relative to the active-decision environment. The estimates show that the proportion of donations at the different defaults increases by a statistically significant 0.2-0.3 percentage points. These figures coincide exactly with the heights of the modes in the top row of Figure 5.

	Change in proportion of donations:			
Treatment	Exactly at the treatment amount	Below the treatment amount	Above the treatment amount	No. Obs.
(1)	(2)	(3)	(4)	(5)
€10	0.002***	-0.001*	-0.001***	341,430
	(0.000)	(0.001)	(0.000)	
€20	0.003***	-0.002***	-0.001***	341,637
	(0.000)	(0.000)	(0.000)	
€50	0.002***	-0.001***	-0.001**	342,163
	(0.000)	(0.000)	(0.000)	

TABLE B.4. Movements to default donation. *Notes:* The table describes the change in the fraction of donations exactly at, below, and above the default donation amount, relative to the active-decision environment. Column 1 lists the default donation treatment. Column 2 (3) [4] depicts the difference in the proportion of donations exactly at (strictly below) [strictly above] the default amount mentioned in column 1. The number of observations is indicated in column 5 and pertains to observations from either the active-decision treatment or the treatment indicated in column 1. Standard errors are clustered at the session level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Columns 3 and 4 address the question where the increased mass of donations at the default is coming from. The two columns disaggregate the figures in column 2 into (net) movements from below the default (column 3) and movements from above the default (column 4), relative to the active-decision treatment. The numbers indicate that, across all treatments, the shift in the distributions to the default amounts comes in roughly equal shares from people who would otherwise have donated less and others who would have donated more than the default.

Online Appendix C: Common Explanations for Default Effects

When differences in default specifications lead people to alter their choices, this is referred to as a "default effect". A variety of psychological mechanisms have been proposed that can give rise to such effects. In this section, we describe what different mechanisms that have featured prominently in the discussion of default effects predict in our setting. Many of these mechanisms have not been fully formalized in the literature, and hence there is some ambiguity (and potential disagreement) about their exact predictions. In our discussion, we try to give a fair account of the different mechanisms and their implications for our setting—sometimes allowing for more than one interpretation of the proposed mechanism and its behavioral consequences.

The relative importance of the various mechanisms will, naturally, depend on the decision environment, and more than one of the psychological motives discussed below may be at play in our setting. While our experiment is not designed to precisely pin down one underlying mechanism, a discussion of different candidates is nevertheless useful to interpret the findings from our experiment. We will hence mainly focus on the mechanisms' predictions for the two main outcomes discussed in our empirical analysis: (i) the impact of defaults on the distributions of donations and codonations—in particular whether we should expect "bunching" of donors at the respective default amounts and/or systematic treatment differences in donation rates—and (ii) how this affects average donation and codonation levels across treatments. An overview of the presented mechanisms and their main predictions can be found in Table C.1.

C.1. **Transaction Costs.** A first motive for why consumers might stick to defaults is direct transaction costs associated with deviating from the default (e.g., Schwartz and Scott 2003). Such costs are unlikely to play an important role in our setting. For one, these costs are essentially zero in online applications, since consumers are in an environment where alternative choices are just "one click away". For another, the costs of filling in alternative donation and codonation amounts seem negligible in comparison to other costs that donors incur to finalize the transaction, such as filling out the contact and payment details in the donation form. Transaction costs may thus contribute to the low overall donation rate that we observe. We would, however, expect no treatment differences in donation or codonation patterns resulting from transaction costs.

	Donations				Codonations				Further effects
	Bunching at default	Average donation level (if default ↗)	Donation rate (extensive margin)	Further distributional effects	Bunching at default	Av. codonation level (if default ↗)	Codonation rate (extensive margin)	Further distributional effects	
Our Data	✓	–	AD = D10 = D20 > D50		✓	↗	C5 > C10 = C15		- Low overall donation rate - Positive correlation in default acceptance across choice dimensions
Transaction Costs	–	–	–		–	–	–		- Low overall donation rate (independent of treatment)
Procrastination	–	–	–		–	–	–		- Low overall donation rate (independent of treatment)
Inattention (I)	✓	↗	AD ≤ D10 = D20 = D50	Changes only exactly at default values: e.g., at €10 and €20 when comparing D10 and D20	✓	↗	–	Changes only exactly at default values	- Positive correlation in default acceptance across choice dimensions - No default effects in donation (codonation) dimension for donors who actively opt out of a given codonation (donation) default.
Inattention (II)	–	–	–		✓	↗	–	Changes only exactly at default values	- No default effects in donation dimension for donors who actively opt out of a given codonation default.
Inattention (III)	✓	↗	AD ≤ D10 = D20 = D50	Changes only exactly at default values	✓	↗	–	Changes only exactly at default values	- Positive correlation in default acceptance across choice dimensions - No default effects in donation dimension for donors who actively opt out of a given codonation default.
Anchoring	(✓)	↗	AD ≤ D10 = D20 = D50	More donations in neighborhood of default	(✓)	↗	AD ≤ D10 = D20 = D50	Increase in neighborhood of default	- Higher average donations (codonations) for higher codonation (donation) defaults
Pure Status Quo	–	–	–		–	–	–		- Low overall donation rate (independent of treatment)
Reference Dependence (linear gain-loss utility)	✓	↗	AD ≤ D10 = D20 = D50	Changes only between defaults: e.g., in [€10, €20] when comparing D10 and D20	✓	↗	–	Changes only between defaults	- Positive correlation in default acceptance across choice dimensions
Information and Recommendations (weighted average signal model)	(✓)	↗	AD ≤ D10 ≤ D20 ≤ D50	First-order stochastic dominance shift at higher defaults	(✓)	↗	C5 ≤ C10 ≤ C15	First-order stochastic dominance shift at higher defaults	
Social Norms	✓	?	?		✓	?	?		

TABLE C.1. Theoretical Mechanisms. *Notes:* The table gives an overview of the theoretical mechanisms discussed in Section B.2 and their main predictions. "AD" denotes the active-decision environment, "D*X*" denotes treatments with a €*X* donation default, "C*X*" denotes treatments with a *X*% codonation default. "✓": mechanism predicts bunching at the default, "(✓)": bunching predicted if additional assumptions are fulfilled (e.g., donors sticking to prominent numbers), "–": no treatment effect predicted.

C.2. **Procrastination.** A second potential source of default effects is a tendency among consumers to delay active choices. Such procrastination is thought to play a key role for default effects in settings like retirement savings or organ donor registration (e.g., Carroll et al. 2009, Johnson and Goldstein 2003). As mentioned in Section 2.2 of the paper, a crucial difference between these settings and ours is that consumers in the former operate against a background of *default rules* that are behaviorally relevant even when consumers remain entirely passive. Procrastination matters in these contexts because when people delay decisions on, say, their organ donor status or savings plan enrollment, the default settings determine their choices.

In contrast, participants in our experiment are confronted with *default options* in a choice environment that is otherwise characterized by active decision-making. Specifically, the default settings in our experiment only become relevant after a user actively enters the online platform, decides on a project to which she wants to contribute, fills out the remainder of the donation form, and confirms the transaction.

A tendency to procrastinate may thus deter people from donating altogether, e.g., because they do not enter the platform in the first place or drop out at some later stage of the decision process. This may lower the overall donation rate on the platform, but there is no obvious reason why this effect would differ across treatments. Procrastination should also have no systematic treatment effects on the distributions of choices along the intensive margin. In particular, it seems implausible that present-biased consumers bear the short-run costs of actively going to the platform, selecting a project, etc., but then do not incur the (small) costs of actively determining the actual donation or codonation amount, only to promptly continue with filling in their address and payment details and confirming the transaction. In sum, procrastination may play an important role for the overall low donation rate, but there should be no systematic treatment differences in donation behavior, purely due to procrastination.

C.3. **Limited Attention.**

C.3.1. *Simple Inattention.* A third reason for why consumers might stick to defaults is that they do not pay (full) attention to the stipulated default and its economic consequences. In what follows, we discuss how inattention among potential donors could influence the results of our experiment. We assume that participants who do not pay attention to a given choice dimension automatically stick to the default in that dimension, whereas attentive donors are not influenced by default specifications. We consider three simple cases: (i) a fraction of potential donors is completely inattentive to both the primary and the secondary choice dimension; (ii) all participants pay full attention to the primary donation decision, but some do not pay attention to the secondary (codonation) dimension; and (iii) some participants are completely inattentive to both dimensions whereas others are only inattentive to the secondary dimension.

First, consider case (i) in which potential donors are either fully attentive or completely inattentive to both choice dimensions. If this is the case, we should observe systematic bunching of donors at the respective default amounts, driven by inattentive types. More specifically, the choice distributions of two treatments with different donation defaults should only differ in the fraction of people contributing exactly the respective default amounts. Moreover, since attentive participants are not influenced by defaults and inattentive ones always stick to the default, there should be no systematic differences in donation rates along the extensive margin, at least for treatments with positive donation defaults.[1] Third, as a result of the two previous effects, we should observe a monotone increase in average donation levels at higher donation defaults (i.e., going from €10 over €20 to €50).[2] Fourth, the impact of defaults in the codonation dimension should be qualitatively similar to those in the donation dimension. In particular, average codonation levels should be highest for the 15% codonation default, intermediate for the 10% default, and lowest for the 5% default, with the differences in averages being exclusively driven by differences in the frequencies of codonations exactly at the default amounts.

Moreover, since potential donors are either fully attentive or inattentive to both choice dimensions, we should observe a strictly positive correlation between individuals' likelihood of sticking to the default in the donation vs. codonation dimension. For the same reason, the model in case

[1] It is less clear how donation rates in the treatments with positive donation defaults compare to those in the active-decision environment. To see why, note that being inattentive to the donation amount is not a viable option in the active-decision treatment: since a contribution of zero is an invalid entry, potential donors are forced to pay attention to the donation decision in this treatment (see Section 2.2 in the paper). If some of the inattentive participants drop out of the donation process after their attention has been called, we might observe a lower donation rate in the active-decision environment, relative to the other treatments.

[2] The comparison to the active-decision treatment is again less clear and depends on how the donation distribution of inattentive types who have been forced to pay attention compares to the one of attentive donors.

(i) predicts that for those participants who actively deviate from a given default in one choice dimension, we should observe no default effect in the *other* choice dimension. For instance, all donors who actively change the donation amount when facing a €10 default are attentive and should thus exhibit no differences in the distributions of codonations for different codonation defaults. Conversely, for those donors who actively deviate from, say, a 10% codonation default, the donation distributions under different default donation values should look exactly the same.

While the simple inattention model of case (i) yields a number of interesting predictions, there is reason to be skeptical about the assumption that a fraction of donors are inattentive to the decision in the donation dimension. After all, making a donation is presumably the main reason for donors to visit the online platform, so the choice of the actual donation amount is likely to be part of a deliberate decision process. We thus consider case (ii) where all participants are fully attentive to the donation dimension but some are inattentive to the codonation dimension. Since everybody pays full attention to the donation decision, this model predicts no default effects in the donation dimension. We should thus observe no differences in donation rates, average donation levels, and the distributions of donations across treatments. Inattentive types, however, still stick to the codonation default. Hence, changing defaults in the codonation dimension has similar effects as in case (i). In particular, we should observe a monotone increase in average codonation amounts at higher defaults, which is exclusively driven by (equally-sized) changes in the proportion of codonors at the respective default values.

Finally, consider case (iii) where some participants are fully attentive, others are only inattentive to the secondary dimension, and a third group is inattentive to both choice dimensions. In this case, our predictions regarding default effects in the donation dimension are qualitatively in line with case (i), and are driven solely by potential donors who are inattentive in both choice dimensions. Similarly, our predictions regarding the codonation dimension are unaltered relative to case (ii), as they are driven solely by the types that are inattentive to that dimension (i.e., the second and third group of participants). Furthermore, as some participants are inattentive to both dimensions, we should also observe a positive correlation between the propensities to stick to defaults in the donation and codonation dimension. Finally, we should still find no default effects in the donation dimension for those donors who deviate from a given default in the codonation dimension. In contrast to case (i), however, we should observe a default effect in codonations even among participants who actively opt out of a certain donation default. This effect is driven by the group of participants who are inattentive only to the secondary dimension.

C.3.2. *Other Attention-related Considerations: Salience, Focusing, and Cognitive Costs.* Closely related to the intuitions behind case (ii) and (iii) above, potential donors may not be fully inattentive, but deliberate more carefully about the primary than the secondary dimension. Codonation decisions may be less salient or out of the focus of potential donors because they are not the main reason for the platform visit, and they generally involve smaller absolute amounts of money. Recent models of salience and focusing (see Bordalo, Gennaioli, and Shleifer 2013 and Kőszegi and Szeidl 2013) argue that dimensions in which alternatives differ more strongly are weighted more heavily in people's decisions.[3] Similarly, studies of cognitive costs maintain that agents tend to think more about dimensions in which there is more at stake (see, for example, Caplin and Dean 2014 and Chetty, Looney, and Kroft 2007). This broad intuition is in line with empirical evidence that people tend to under-appreciate variations in add-on costs such as shipping and handling, sales taxes, etc. relative to the variation in the primary purchase price (Hossain and Morgan 2006, Chetty, Looney, and Kroft 2009).[4]

While there is no model of partial awareness or salience that speaks directly to our default setting, if one believes that subjects are more likely to be influenced by defaults in dimensions on which they focus less, one would expect default effects to be particularly pronounced in the codonation dimension. In the extreme case in which some subjects do not focus at all on the codonation dimension but everybody puts sufficient weight on the primary donation dimension, we are back

[3]To be able to formally apply these models we would first need to specify the relevant choice (or consideration) set of potential donors. In principle, people could donate or codonate large sums and there is no theoretical model delineating how to construct the relevant consideration set. The main intuition that agents focus more on "important" choice dimensions, however, loosely suggests that defaults may be more relevant in the codonation dimension, also because the codonation is automatically calculated as a percentage fraction of the main donation.

[4]This effect may be weaker in our case since Betterplace is committed to transparency and hence the additional payment is not shrouded. Rather, codonations are clearly displayed in the calculation of the total contribution on the payment page, and the presence of a default for codonations may even raise the attention towards this dimension (see Figure 2). Participants may, however, still attach less weight to the codonation dimension as it generally involves lower stakes.

to case (ii) of the simple inattention model in which default effects should exclusively be observed for codonations.

C.4. **Anchoring.** Another frequently discussed reason for why defaults are behaviorally relevant is that they may act as "anchors" that people use as a starting point in their decision process (Tversky and Kahneman 1974, Johnson and Schkade 1989, Ariely, Loewenstein, and Prelec 2003). To the extent that such anchors influence individuals' choices, we should observe higher average contributions in treatments with higher default values. This effect should apply to both the donation and codonation dimensions. Moreover, since anchoring effects can emerge from arbitrary numbers that are not directly decision-relevant (e.g., social security numbers influencing initial valuations of goods and hedonic experiences in Ariely, Loewenstein, and Prelec 2003), we should observe "spillovers" between the donation and codonation dimension. That is, an anchoring-based explanation of default effects would predict that higher donation defaults yield higher average donations as well as higher codonations. Similarly, higher default values in the codonation dimension should also increase both codonations and donations.

In contrast to the case of simple inattention discussed above, an anchoring-based theory does not necessarily predict an increase in the frequency of contributions at the default amount itself. Rather, it predicts that defaults increase the number of contributions that lie in the neighborhood of the default—or anchor—from which people adjust. However, because we know from historical data on the online platform that donors tend to contribute "prominent" numbers such as €5, €10, etc., and all our donation defaults correspond to such prominent numbers (e.g., Albers 2002), an increase in the neighborhood is likely to correspond to an increase at the default amount itself. If this is true, anchoring also predicts that the number of non-donors (as well as non-codonors) should be highest in the active-decision environment where the donation field is initially set to zero.

C.5. **Status-quo Bias and Reference Points.** A next factor that is often brought forward as a potential source of default effects are endowment effects or status quo biases among decision makers (e.g., Johnson, Bellman, and Lohse 2002). Strictly speaking, the status quo in our setting is that potential donors are endowed with some money and have not (yet) made a donation. As this holds in all of our treatments, a literal interpretation of a status quo bias suggests that there should be no default effects in our setup (and, similarly, in other settings that involve "default options" rather than "default rules").[5]

Some authors, however, have argued that defaults may constitute an "implicit" endowment (e.g., Dinner et al. 2011) or, more generally, they could induce a reference point to which decision makers compare other alternatives. Together with loss aversion, such reference-dependent preferences may lead to default effects in our setting. In the simplest possible setup in which (i) non-reference-dependent utility is additively separable across the donation dimension and a monetary one (as well as the codonation dimension and money), (ii) potential donors bracket narrowly (i.e., they consider the decisions in the donation and codonation dimension in isolation), (iii) the reference point in each decision dimension is equal to the outcome that is realized when the individual sticks to the default option, and (iv) the gain-loss utility function is linear, the implicit endowments stipulated by defaults may indeed affect donors' behavior.

Intuitively, when changing the default in the donation dimension from a lower to a higher amount, the marginal utility of donating increases at any point in between the two default amounts (i.e., in the interval between the old and the new reference point). Under the old reference point, donating an extra unit of money gives a donor in this interval an extra gain in the donation dimension at the cost of a loss in the money dimension. Under the new reference point, however, the same increase in the donation amount reduces the loss felt in the donation dimension (compared to the new—higher—reference point), at the mere cost of forgoing a gain in the money dimension. Because losses matter more than equally-sized gains, this increases the marginal utility of donating and, hence, should lead donors in this interval to increase the amount they give. Outside of the described interval (i.e., below the lower and above the higher reference point), the marginal utility of donating—and therefore donors' behavior—remains unchanged: under both reference points, donating an extra unit of money is viewed similarly as a gain or as a loss. This also implies that we

[5] Similarly, models of expectation-based reference points (Kőszegi and Rabin 2006), which specify the reference point as the decision maker's rationally expected outcome, predict no effect of defaults on the set of personal equilibria in our setting, because they do not affect the donor's choice set.

should observe no extensive-margin differences in donation rates for the treatments with positive default donation levels.[6]

As a result of the described effects, an increase in the donation default should lead to a monotone increase in the average amount donated. Furthermore, because the overall utility has a kink at the reference point, the model predicts bunching at the respective default value. Since agents bracket narrowly, the described effects should be qualitatively similar in the codonation dimension, with the added subtlety that the reference point in the codonation dimension also depends on the donation default (as it is calculated as a percentage fraction of that default). Specifically, holding the donation default constant, an increase in the codonation default should increase average codonation levels, with the difference in averages being driven by changes in the behavior of participants between the reference points. Finally, as we explain in more detail in Section C.9 below, in which we discuss the behavioral effects of reference dependence more formally, one may also expect a positive correlation in donors' likelihood to stick to defaults in the two choice dimension.

Our discussion in Section C.9 also illustrates that additional countervailing effects may arise in a more general framework of reference dependence that involves diminishing sensitivity in the gain-loss utility function, broad bracketing across choice dimensions, or alternative reference-point specifications in the codonation dimension. While the model loses predictive power in these more flexible specifications (in particular regarding the presence and direction of treatment difference in average donation and codonation levels), it still predicts that we should observe systematic bunching of donors at the reference points that are induced by the defaults. Moreover, for the case of broad bracketing, a reference-dependent model can also account for spillovers between both treatment dimensions, so that higher donation default can induce higher codonation levels, and vice versa.

C.6. **Information and Recommendations.** Another prominent argument for why default specifications affect people's choices is that they may convey some information on what the default-setting institution—in our case, the online platform or charity—considers to be a "good" choice (Madrian and Shea 2001, McKenzie, Liersch, and Finkelstein 2006, Altmann, Falk, and Grunewald

[6]If donors interpret the zero displayed in the donation field of the active-decision treatment as a reference point, we may, however, observe lower donations rates in this treatment.

2013). In its simplest form, this mechanism predicts that average donations as well as average codonations increase monotonically in the respective default amounts. More precisely, for the case of a donor who makes her donation decision based on a weighted average of the default and some own private signal for her contribution level, we would expect a first-order stochastic dominance shift in the distribution of donations for higher default donation levels. Moreover, we should also observe a higher (extensive-margin) donation rate at higher donation defaults, since potential donors who consider the default a recommendation have a higher willingness to give when the recommended action increases. Note that, as in the case of anchoring discussed above, an information-based mechanism does not necessarily imply bunching or pronounced spikes exactly at the default amounts (although it may if people stick to "prominent" numbers).

If some donors are systematically less informed than others, then these donors may react more strongly to defaults in both dimensions. In the extreme case in which uninformed donors follow the recommendation perfectly, an information-based mechanism would predict a strong positive correlation in the propensity to stick to the defaults for donations and codonations. The degree to which defaults influence decisions through a recommendation-based mechanism, however, may also plausibly differ across choice dimensions. For instance, if people who visit the website in order to make a donation have a relatively precise idea of how much they want to give (i.e., they put a lot of weight on their private donation signal) but did not seriously consider the codonation dimension beforehand, they may put more weight on the recommendation in the codonation dimension. Conversely, potential donors may also be less inclined to follow defaults in the codonation dimension, e.g., if they believe the platform providers to be more partisan in this dimension (because the platform directly benefits from higher codonation levels).

If we allow for more general information structures or decision-making processes that people may follow, the predictions on how participants react to different defaults or recommendations become more ambiguous. For example, suppose that a potential donor decides to give based on whether a project is suitable for her donor type and based on the amount of money needed per donor. A higher default may then signal to the donor that she should give a higher amount, but it may also signal along the other dimension that this type of project is better suited for wealthier or more generous donor types. In the latter case, a higher default amount could lead the participant to abstain from donating altogether. Alternatively, a potential donor could conclude from a high default amount that the platform (or the charity) is greedy or non-trustworthy, which again could decrease her willingness to give. As these examples illustrate, it is generally impossible to derive specific and unambiguous predictions on how defaults affect behavior through an information- or recommendation-based channel, without having a model that specifies the economic environments or games that a potential donor deems possible and tries to make inferences about when seeing the default.

C.7. **Social Norms.** Related to an information-based explanation of default effects is the idea that defaults may send a signal about prevailing social norms or may themselves shape these norms (e.g., Altmann and Falk 2011). If this is the case, defaults could affect the behavior of potential donors who care about adhering to social norms. The exact behavioral consequences depend on the specific norm that is conveyed through the default, and the resulting costs from norm deviations.

One plausible scenario in our context is that defaults may send a signal to potential donors about the minimum contribution level that is socially acceptable. If this is the case and if (a fraction of) potential donors care about adherence to the norm, differences in default specifications across treatments have clear implications for the distributions of donations along the intensive margin. Specifically, while contributions above the default are in line with the social norm, contributions below this threshold violate the norm and might thus be costly for the donor, e.g., due to image concerns or (self-)signaling motives (e.g., Benabou and Tirole 2006, Ariely, Bracha, and Meier 2009, Gneezy et al. 2012). If these costs are sufficiently high, we should observe relatively few people donating amounts (right) below the default in a given treatment. In contrast, donations above the respective default should not be affected, as the norm only stipulates a minimum acceptable amount. Comparing two treatments with different donation defaults, we should then find no differences in the distributions of donation above the higher of the two default amounts. At the same time, we should observe spikes in the distributions of donations at the respective default values that are driven by drops in the number of donations (right) below the donation default in a given treatment.

For the extensive margin, some findings in the literature suggest that opting out of the donation process altogether does not constitute a norm violation, since this might not signal that the participant *would* have given less than the social norm (see Dana, Cain, and Dawes 2006 and DellaVigna, List, and Malmendier 2012). If this is the case, we might observe a decrease in donation rates at the extensive margin for higher donation or codonation defaults. With contributions increasing along the intensive margin and donation rates along the extensive margin decreasing in defaults, the net effect of an increase in defaults on average donation (and codonation) levels is ambiguous. Conditional on donating, however, we should observe an increase in average donations at higher default values if defaults signal a minimum contribution threshold.

Another possibility is that defaults do not signal a *minimum* acceptable contribution level, but rather stipulate a donation norm to which potential donors want to conform *exactly*. If this is the case, then both negative and positive deviations from the default will constitute a norm violation and are therefore costly for such potential donors. A given donation default might then lead some donors to increase their donation, while others who would otherwise have given more than the default amount might reduce their contributions. As a result, a default theory based on such norm conformity would predict movements towards the default from above and below along the intensive margin, with ambiguous net effects of a change in defaults on average donation and codonation levels across treatments.[7]

As the two previous examples illustrate, the specific predictions of a norm-based theory of default effects crucially depend on the details and scope of the stipulated social norm. The same holds for the question of whether default effects are expected to be similar or different in the donation or codonation dimension. If, for instance, potential donors care strongly about social norms regarding charitable giving, but only little about "tipping" norms in the codonations dimension, we should observe particularly strong default effects in the donation dimension. The opposite scenario, however, is also conceivable. Lastly, to derive precise predictions for a norm-based model of default effects, one would also need to specify how defaults interact with pre-existing social norms and

[7] Such a theory of conformity would also predict the donation rate to be lowest in the active-decision treatment if participants interpret a contribution of zero as the social norm. This, however, seems relatively implausible in a charitable-giving context.

preferences that potential donors might "bring to the platform". For instance, if potential donors have very strong prior norms regarding charitable contributions, defaults might have a relatively weak impact on the perceived social norm and, consequently, on donors' behavior.

C.8. **Which Mechanisms are Consistent with the Experimental Results?** Table C.1 summarizes the empirical predictions of the considered mechanisms and compares them to the results of our experiment. A successful theory should be consistent with the two main results from Sections 3.1 and 3.2 in the paper—that defaults have strong distributional effects for both donations and codonations, but at the same time no systematic impact on average donation levels.

The table indicates that most of the mechanisms discussed above are inconsistent with the simultaneous observation of these two outcomes. More specifically, the simple models of consumer inattention, reference-dependent preferences with linear gain-loss utility, or anchoring all predict the observed bunching at the defaults, but in contrast to our empirical findings, they also predict a monotone increase of average donation levels at higher default values. The same holds for an information- or recommendation-based model if donation decisions are based on a weighted average of the default and donors' private signals. Hence, these individual mechanisms as well as combinations thereof can not explain our findings. Furthermore, explanations based on the notion that consumers avoid making active decisions because of transaction costs, procrastination, or status-quo biases also seem of limited relevance. These factors might be important for understanding the overall low donation rate on the platform and they are also consistent with not finding average treatment effects for donations, but we would also expect no systematic treatment differences for the distributions of donations, based purely on these mechanisms.

Turning to the comparison of default effects in the donation and codonation dimension, the fact that we observe a relatively strong correlation in the likelihood to stick to defaults in both choice dimensions suggests an explanation in which some types of donors are systematically more affected by defaults than others (see also the discussion in Section 4 of the paper). Furthermore, the observation that donation levels slightly increase in the codonation default is reminiscent of an anchoring-based mechanism or specific formulations of reference dependence, which both predict such spillover effects. As discussed in Sections 3.2 and 3.3, however, the evidence for spillover effects in our data is rather weak and unsystematic (e.g., we observe the effects only for some treatment pairs, but not for others). Moreover, other key predictions of the mentioned mechanisms—such as the monotone increase in donation levels at higher defaults—are not borne out by our data (see Table C.1). Finally, the fact that we observe particularly pronounced default effects in the codonation dimension might suggest that potential donors pay less attention to this dimension (e.g., since stakes are much smaller). This finding, however, may also be related to factors concerning the design of the donation form (e.g., codonations being presented as percentages in a drop-down menu, donations being determined as absolute amounts in a free-form format). It is thus difficult to directly compare the relative strength of default effects across the two choice dimensions.

In sum, none of the simple mechanisms discussed in this section can account for all of our empirical findings. With more flexible notions of limited attention, more general information structures in recommendation-based models, or non-linear gain-loss utility in case of reference-dependent preferences, models of limited attention, information transmission, or reference dependence may ultimately be able to rationalize our data. The same holds for an explanation based on social norms—at least under specific assumptions regarding the nature of and behavioral reactions to these norms. However, while these more involved versions of the models provide a possible account of our main empirical findings, they are all consistent with a very wide range of behavioral responses and, hence, lack predictive power (e.g., regarding the presence or absence of overall treatment effects).

C.9. **Reference-dependent Preferences and Default Effects.** In this subsection, we provide a brief formalization of the idea that defaults may affect behavior of reference-dependent agents by defining an implicit endowment to which agents compare available choice alternatives. Suppose that agents have a quasi-linear material utility function that is additively separable in the following way: $u^X(x) + u^Y(y) - (x + y)$, where x denotes the amount donated, y denotes the codonation, and $-(x + y)$ captures forgone consumption of all other goods. Furthermore, suppose that u^X and u^Y are twice differentiable, strictly concave utility functions whose first derivative tends to zero as the amount donated (respectively codonated) tends to infinity.

Overall utility is the sum of the above material utility and a gain-loss utility function that depends on the reference points induced by the defaults in the donation and codonation dimension. Let r^X, r^Y denote the reference points in the donation and codonation dimensions, respectively. Suppose first that potential donors bracket narrowly, i.e., they have separate mental accounts for money donated and money codonated. For each $dim = X, Y, MX, MY$, let μ^{dim} be a dimension-specific gain-loss utility function satisfying the standard assumptions that give rise to a Kahneman-Tversky-type value function (Kahneman and Tversky 1979).[8] Normalizing the material utility of not donating to zero, the total utility of a potential donor choosing to donate (x, y) is then given by

$$\begin{aligned} U(x,y) &= u^X(x) + u^Y(y) - (x+y) \\ &\quad + \mu^X(u^X(x) - u^X(r^X)) + \mu^Y(u^Y(y) - u^Y(r^Y)) + \mu^{MX}(r^X - x) + \mu^{MY}(r^Y - y). \end{aligned}$$

Consider first the case of two-part linear gain-loss utility functions, where the slope for gains is denoted by $\eta^{dim} > 0$ and that for losses is given by $\eta^{dim} l^{dim}$ for each $dim = X, Y, MX, MY$. For any donation level $x < r^X$, the marginal utility of donating is then given by

$$u^{X\prime}(x)[1 + \eta^X l^X] - [1 + \eta^{MX}],$$

[8]Specifically, we follow Bowman, Minehart, and Rabin 1999 and assume the value function satisfies: (i) μ^{dim} is increasing; (ii) each μ^{dim} is differentiable everywhere except at zero; (iii) for each μ^{dim} if $b > a > 0$, then $\mu^{dim}(b) + \mu^{dim}(-b) < \mu^{dim}(a) + \mu^{dim}(-a)$; and (iv) each μ^{dim} satisfies $\lim_{a \searrow 0} \frac{(\mu^{dim})'(-a)}{(\mu^{dim})'(a)} \equiv l^{dim} > 1$.

and the marginal utility at any level $x > r^X$ is

$$u^{X\prime}(x)[1 + \eta^X] - [1 + \eta^{MX} l^{MX}].$$

First note that the marginal utility has a concave kink at the reference point r^X and, hence, one would expect bunching at the reference point (i.e., the donation default) if there is preference heterogeneity in the population and the default lies in the support of the donation distribution. Second, an increase in the reference point from r^X to $\hat{r}^X$ affects neither the marginal utility above $\hat{r}^X$ nor that below r^X, but it does strictly raises the marginal utility over the interval $(r^X, \hat{r}^X)$. As a result, this formalization predicts an increase in average contributions in response to higher donation defaults. Moreover, the change in the distribution of donations should occur exclusively over the interval $[r^X, \hat{r}^X]$ and corresponds to a first-order stochastic dominance shift. This also implies that there are no extensive-margin differences in donation rates among treatments with positive default donation amounts. We may, however, observe lower donations rates in the active-decision treatment if donors interpret the zero displayed in the donation field of this treatment as a reference point.

Now consider how the above conclusions are affected when the gain-loss utilities μ^{dim} exhibit diminishing sensitivity. In this case, the marginal utility of donating is given by

$$u'(x)[1 + \mu^{X\prime}(u^X(x) - u^X(r^X))] - [1 + \mu^{MX}(r^X - x)].$$

For a given donation level $x < r^X$, an increase in the reference point from r^X to $\hat{r}^X$ has two effects. First, it increases the loss to $u^X(x) - u^X(\hat{r}^X)$ in the donation dimension and thereby, due to diminishing sensitivity, decreases the marginal utility of donating. Second, it increases the gain to $\hat{r}^X - x$ in the money dimension, which thereby decreases the marginal utility of keeping money and, hence, increases the marginal utility of donating. The overall effect is therefore ambiguous. Analogous reasoning implies that the effect on the marginal utility is ambiguous for donation levels above the reference point $\hat{r}^X$. Hence, both the distribution of donations as well as the average donation level change in an ambiguous way. Since, however, the discontinuity of the marginal utility is always at the reference point, this model still predicts bunching at the respective default donation levels. Furthermore, since the involved material utilities should be small for most participants in our experiment (who give relatively small amounts of money), it seems plausible that the effect of loss aversion dominates the one of diminishing sensitivity and that, consequently, the two-piece linear case described above is likely to be a good approximation.

A similar intuition applies to the codonation dimension with an added subtlety regarding the specification of the reference point for agents who do not donate the default donation amount. It is tempting to specify $r^Y = c\% \times r^X$, where $c\%$ is the default codonation percentage. Note that in this case, however, donors who actively decide to opt out of the donation default (e.g., choose $x =$ €10 when the default is $r^X =$ €20) need to engage in an active choice to hit the reference point in the codonation dimension (e.g., if $c = 10$ in the above example, they would need to increase the codonation percentage to 20% in order to codonate $r^Y = 2$). We would think of choices along these lines as very strong evidence for the described type of reference-dependent behavior, but neither expect (nor actually observe) it in our data. A slightly weaker implication is that donors should either stick to both defaults or deviate from both, i.e., we should observe a positive correlation of default adherence in the two choice dimensions.

Things become even more subtle if donors bracket the gain-loss utility from money donated and codonated jointly, i.e., they have a utility function of the following form:

$$u^X(x) + u^Y(y) - (x + y) + \mu^X(u^X(x) - u^X(r^X)) + \mu^Y(u^Y(y) - u^Y(r^Y)) + \mu^M(r^X + r^Y - x - y).$$

Then the marginal utility of donating will in general have two concave kinks, one at $x = r^X$ and one at $x + y = r^X + r^Y$, which coincide only in the case in which $y = r^Y$. We would thus, for example, expect two bunching points for donors that codonate zero—one at the donation default and one at $r^X + r^Y$. Specifying r^Y as above, for example, this would imply when $r^X = 20$ and the default codonation is 10%, that such donors bunch at donation amounts of €20 and €22. More generally, in this case we should observe spillovers between both treatment dimensions, so that the distribution of donations should vary with the codonation default.

Online Appendix D: Derivations and Supplementary Estimates for the Structural Model

D.1. **Derivation of the likelihood function.** As established in the main text (see equation 2), the agent's optimal donation $x^o \in \{0, \rho, d\}$. In particular, if the agent is an ungenerous type ($\rho = 0$), her optimal donation is $x^o = 0$. Otherwise, if the agent is a generous type and faces no deviation costs, then the optimal donation is $x^0 = \rho$. If the agent faces deviation costs, and $\rho = 0$, then the optimal donation is $x^0 = 0$. Similarly, if the agent faces deviation costs, and $\rho = d$, then the optimal donation is $x^0 = d$. If the agent faces deviation costs, and $\rho > 0$, $\rho \neq d$, then x^0 can be either 0, d, or ρ.

We index agents who act as if they are not subject to deviation costs δ, by $z = 0$. Agents who suffer positive deviation costs are indexed by $z = 1$.The total probability of donating a quantity x, denoted as $\Pr(X = x)$, is equal to (using the law of total probability):

$$\Pr(X = x) = \Pr(z = 0)\Pr(X = x\,|z = 0) + \Pr(z = 1)\Pr(X = x\,|z = 1)\ .$$

Then,

$$\begin{aligned}
\Pr(X = x) \quad &= \quad \lambda_1 \Pr(\rho = x) + (1 - \lambda_1)\Big[\Pr(\rho = 0\,|z = 1)\ \Pr\Big(X = x\,\Big|z = 1, \rho = 0\Big) \\
&+ \quad \Pr(\rho = d\,|z = 1)\ \Pr\Big(X = x\,\Big|z = 1, \rho = d\Big) \\
&+ \quad \sum_{\tilde{\rho}\neq 0, \tilde{\rho}\neq d} \Pr(\rho = \tilde{\rho}\,|z = 1)\ \Pr\Big(X = x\,\Big|z = 1, \rho = \tilde{\rho}\Big)\ \Big].
\end{aligned}$$

Because ρ is independent of z, this can be written as

$$\begin{aligned}
\Pr(X = x) \quad &= \quad \lambda_1 \Pr(\rho = x) + (1 - \lambda_1)\Big[\Pr(\rho = 0)\Pr\Big(X = x\,\Big|z = 1, \rho = 0\Big) \\
&+ \quad \Pr(\rho = d)\Pr\Big(X = x\,\Big|z = 1, \rho = d\Big) \\
&+ \quad \sum_{\tilde{\rho}\neq 0, \tilde{\rho}\neq d} \Pr(\rho = \tilde{\rho})\Pr\Big(X = x\,\Big|z = 1, \rho = \tilde{\rho}\Big)\ \Big].
\end{aligned}$$

Note that the first two lines are straightforward to solve for, using the fact that an ungenerous type never donates and that an agent with $\rho = d$ will always donate the default, regardless of facing deviation costs. For solving the last object, it is useful to define the following events:

$$\mathrm{A} = \left\{(\alpha, \delta, \rho) \quad \text{s.t.} \quad \alpha > \delta - \frac{\rho^2}{2}\right\}.$$

The event A denotes the event where the utility of the agent from donating $x = \tilde{\rho}$ is greater than from the opting out of the donation process all together.

$$\mathrm{B} = \{(\delta, \rho) \quad \text{s.t.} \quad \delta < \Delta(\rho, d)\}.$$

The event B denotes the event where the utility of the agent from donating $x = \tilde{\rho}$ is greater than the utility of donating the default.

$$\mathrm{C} = \left\{(\alpha, \delta, \rho) \quad \text{s.t.} \quad \alpha > \frac{d^2}{2} - \rho d \quad \right\}.$$

The event C denotes the event where the utility of the agent from donating the default is greater than the utility of opting out all together. In what follows, we will consider several cases.

D.1.1. *Case 1.* $x = 0$

Let's first consider the case where x is equal to zero. The probability for this case can be written as follows:

$$\Pr(X = 0) = \Pr(\rho = 0) + (1 - \lambda_1)\left[\sum_{\rho \neq 0} \Pr(\rho = \tilde{\rho}) \Pr\left(X = 0 \middle| z = 1, \rho = \tilde{\rho}\right)\right].$$

For an agent with $\rho = \tilde{\rho}$, $\tilde{\rho} \neq d$ and $\tilde{\rho} > 0$ to opt out of the donation process altogether, the agent needs to be better off than when donating $x = \tilde{\rho}$ or $x = d$. This is the case when the two events A^c and C^c hold.

$$\mathrm{A}^c \cap \mathrm{C}^c = \left\{(\alpha, \delta, \rho) \quad \text{s.t.} \quad \delta > \frac{\rho^2}{2} + \alpha \quad \text{and} \quad \alpha < \frac{d^2}{2} - \rho d\right\}.$$

Then,

$$\Pr\left(X = 0 \middle| z = 1, \rho = \tilde{\rho}\right) = \Pr\left(\mathrm{A}^c \cap \mathrm{C}^c \middle| \rho = \tilde{\rho}\right),$$

$$\Pr\left(\mathrm{A}^c \cap \mathrm{C}^c \middle| \rho = \tilde{\rho}\right) = \Pr\left(\mathrm{A}^c \middle| \mathrm{C}^c, \rho = \tilde{\rho}\right) \Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right).$$

The conditional probability of A^c given C^c and ρ can be written as:

$$\Pr\left(\mathrm{A}^c \middle| \mathrm{C}^c, \rho = x\right) = \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = x\right)} \left(\int_0^{\max(0, \frac{d^2}{2} - \tilde{\rho} d)} \int_{\frac{\rho^2}{2} + \alpha}^{\infty} f_{\alpha,\delta}(\alpha, \delta)\, d\alpha\, d\delta \right).$$

Where $f_{\alpha,\delta}(\alpha, \delta)$ is the joint density distribution of α and δ. Since α and δ are independent, the joint density distribution can be written as:

$$\Pr\left(\mathrm{A}^c \middle| \mathrm{C}^c, \rho = \tilde{\rho}\right) = \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)} \left(\int_0^{\max(0, \frac{d^2}{2} - \tilde{\rho} d)} f_\alpha(\alpha) \int_{\frac{\rho^2}{2} + \alpha}^{\infty} f_\delta(\delta) d\delta\, d\alpha \right),$$

where $f_\delta(\delta) = \lambda_2 e^{-\lambda_2 \delta}$ and $f_\alpha(\alpha) = \lambda_3 e^{-\lambda_3 \alpha}$ are the probability density function of δ and α respectively. Then,

$$\begin{aligned}
\Pr\left(\mathrm{A}^c \middle| \mathrm{C}^c, \rho = \tilde{\rho}\right) &= \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)} \left(\int_0^{\max(0, \frac{d^2}{2} - \tilde{\rho} d)} \lambda_3 e^{-\lambda_3 \alpha} \int_{\frac{\tilde{\rho}^2}{2} + \alpha}^{\infty} \lambda_2 e^{-\lambda_2 \delta}\, d\delta\, d\alpha \right) \\
&= \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)} \left(\int_0^{\max(0, \frac{d^2}{2} - \tilde{\rho} d)} \lambda_3 e^{-\lambda_3 \alpha} \left[-e^{-\lambda_2 \delta} \right]_{\frac{\tilde{\rho}^2}{2} + \alpha}^{\infty} d\alpha \right) \\
&= \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)} \left(\int_0^{\max(0, \frac{d^2}{2} - \tilde{\rho} d)} \lambda_3 e^{-\lambda_3 \alpha} e^{-\lambda_2 (\frac{\tilde{\rho}^2}{2} + \alpha)}\, d\alpha \right) \\
&= \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)} \left(\int_0^{\max(0, \frac{d^2}{2} - \tilde{\rho} d)} \lambda_3 e^{-(\lambda_3 + \lambda_2)\alpha} e^{-\lambda_2 \frac{\tilde{\rho}^2}{2}}\, d\alpha \right).
\end{aligned}$$

For the case that $\tilde{\rho} < \frac{d}{2}$:

$$\begin{aligned}
\Pr\left(\mathrm{A}^c \middle| \mathrm{C}^c, \rho = \tilde{\rho}\right) &= \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)} \left[\frac{-\lambda_3}{(\lambda_3 + \lambda_2)} e^{-(\lambda_3+\lambda_2)\alpha} e^{-\lambda_2 \frac{\tilde{\rho}^2}{2}}\right]_0^{\frac{d^2}{2} - \tilde{\rho} d} \\
&= \frac{1}{\Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)} \left(\frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-\lambda_2 \frac{\tilde{\rho}^2}{2}} - \frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-(\lambda_3+\lambda_2)(\frac{d^2}{2} - \tilde{\rho} d)} e^{-\lambda_2 \frac{\tilde{\rho}^2}{2}}\right) \\
&= \frac{1}{(1 - e^{-\lambda_3(\frac{d^2}{2} - \tilde{\rho} d)})} \left(\frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-\lambda_2 \frac{\tilde{\rho}^2}{2}} - \frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-\lambda_3(\frac{d^2}{2} - \tilde{\rho} d)} e^{-\lambda_2 \Delta(\tilde{\rho}, d)}\right).
\end{aligned}$$

Now using that $\Pr\left(\mathrm{A}^c \cap \mathrm{C}^c \middle| \rho = \tilde{\rho}\right) = \Pr\left(\mathrm{A}^c \middle| \mathrm{C}^c, \rho = \tilde{\rho}\right) \Pr\left(\mathrm{C}^c \middle| \rho = \tilde{\rho}\right)$,

$$\Pr\left(\mathrm{A}^c \cap \mathrm{C}^c \middle| \rho = \tilde{\rho}\right) = \frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-\lambda_2 \frac{\tilde{\rho}^2}{2}} - \frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-\lambda_3(\frac{d^2}{2} - \tilde{\rho} d)} e^{-\lambda_2 \Delta(\tilde{\rho}, d)}.$$

Note that for $\rho > d/2$ this probability is equal to zero, hence:

$$\Pr(X = 0) = \Pr(\rho = 0) + (1 - \lambda_1) \sum_{\rho > 0}^{\lfloor \frac{d}{2} \rfloor} \Pr(\rho = \tilde{\rho}) \left(\frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-\lambda_2 \frac{\tilde{\rho}^2}{2}} - \frac{\lambda_3}{(\lambda_3 + \lambda_2)} e^{-\lambda_3(\frac{d^2}{2} - \tilde{\rho} d)} e^{-\lambda_2 \Delta(\tilde{\rho}, d)}\right),$$

where $\lfloor\quad\rfloor$ is defined as the floor function, floor(v)=$\lfloor v \rfloor$, which takes as an input a real number v (here $\frac{d}{2}$) and returns as an output the greatest integer less than or equal to v.

D.1.2. *Case 2.* $x = d > 0$

Let's next look at the case where the agent's contribution x is equal to the default d. The probability for this case can be written as follows:

$$\Pr(X = d) = \lambda_1 \Pr(\rho = d) + (1 - \lambda_1) \left[\sum_{\tilde{\rho} \neq 0} \Pr(\rho = \tilde{\rho}) \Pr\left(X = d \,\middle|\, z = 1, \rho = \tilde{\rho}\right)\right].$$

For a generous agent with $\rho \neq d$ and to donate d, the agent needs to be better off than when donation the $x = \tilde{\rho}$ or to opt out completely. This is the case when the two events B^c and C hold.

$$\mathrm{B}^c \cap \mathrm{C} = \left\{(\alpha, \delta, \rho) \quad \text{s.t.} \quad \delta > \Delta(\rho, d) \quad \text{and} \quad \alpha > \frac{d^2}{2} - \rho d\right\}.$$

$$\Pr\left(X = d \middle| z = 1, \rho = \tilde{\rho}\right) = \Pr\left(\mathrm{B}^c \cap \mathrm{C} | \rho = \tilde{\rho}\right).$$

Conditional on ρ, the two events are independent and we can hence apply the multiplication rule for independent events:

$$\Pr\left(\mathrm{B}^c \cap \mathrm{C} | \rho = \tilde{\rho}\right) = \Pr\left(\mathrm{C} | \rho = \tilde{\rho}\right) \Pr\left(\mathrm{B}^c | \rho = \tilde{\rho}\right),$$

which can be written as:

$$\Pr\left(\mathrm{B}^c \cap \mathrm{C} | \rho = \tilde{\rho}\right) = \begin{cases} e^{-\lambda_3(\frac{d^2}{2} - \tilde{\rho}d)} e^{-\lambda_2 \Delta(\tilde{\rho}, d)}, & \text{for } 0 < \tilde{\rho} < \frac{d}{2} \\ e^{-\lambda_2 \Delta(\tilde{\rho}, d)}, & \text{for } \tilde{\rho} \geq \frac{d}{2}, \end{cases}$$

which we then insert in the probability of donating d:

$$\Pr\left(X = d\right) = \lambda_1 \Pr\left(\rho = d\right) + (1 - \lambda_1) \left[\sum_{\tilde{\rho} > 0}^{\lfloor \frac{d}{2} \rfloor} f(\tilde{\rho}) e^{-\lambda_3(\frac{d^2}{2} - \tilde{\rho}d)} e^{-\lambda_2 \Delta(\tilde{\rho}, d)} + \sum_{\tilde{\rho} \geq \frac{d}{2}}^{\infty} f(\tilde{\rho}) e^{-\lambda_2 \Delta(\tilde{\rho}, d)} \right].$$

D.1.3. *Case 3.* $x > 0, x \neq d$

Let's now look at the case where x is greater than 0, but differs from the default. The probability for this case can be written as follows:

$$\Pr\left(X = x \middle| x > 0, x \neq d\right) = \lambda_1 \Pr\left(\rho = x\right) + (1 - \lambda_1) \left[\sum_{\tilde{\rho} \neq 0, \tilde{\rho} \neq d} \Pr\left(\rho = \tilde{\rho}\right) \Pr\left(X = x \middle| z = 1, \rho = \tilde{\rho}, x > 0, x \neq d\right) \right].$$

This is because, for any $x > 0$ and $x \neq d$, $\Pr\left(X = x \middle| z = 1, \rho = 0\right) = 0$ and $\Pr\left(X = x \middle| z = 1, \rho = d\right) = 0$. Since a necessary condition to donate $x > 0, x \neq d$ is that $\rho = x$.
Therefore, $\Pr\left(X = x \middle| z = 1, \rho = \rho', x > 0, x \neq d\right) = 0 \quad \forall \quad \rho' \neq x$.
We can then rewrite this as follows:

$$\Pr\left(X = x \middle| x > 0, x \neq d\right) = \lambda_1 \Pr\left(\rho = x\right) + (1 - \lambda_1) \left[\Pr\left(\rho = x\right) \Pr\left(X = x \middle| z = 1, \rho = x, x > 0, x \neq d\right) \right].$$

Now, for an agent with $\rho = x$ and $z = 1$ to donate x, the agent needs to be better off than when donation the default or to opt out completely. This is the case when the two events A and B hold.

$$\begin{aligned}\Pr\left(X = x \middle| z = 1, \rho = x, x > 0, x \neq d\right) &= \Pr\left(\mathrm{A} \cap \mathrm{B} \middle| \rho = x\right) \\ &= \Pr\left(\mathrm{A} \middle| \mathrm{B}, \rho = x\right) \Pr\left(\mathrm{B} \middle| \rho = x\right).\end{aligned}$$

Note that for an agent with $\rho \geq \frac{d}{2}$, it is never optimal to opt out of the donation process completely, hence:

$$\Pr\left(\mathrm{A} \cap \mathrm{B} \middle| \rho = x\right) = \Pr\left(\mathrm{B} \middle| \rho = x\right) \quad \text{if} \quad \rho \geq \frac{d}{2}.$$

Now we compute the objects $\Pr\left(\mathrm{B} \middle| \rho = x\right)$ for $x \geq \frac{d}{2}$ and $x \neq d$, and $\Pr\left(\mathrm{A} \middle| \mathrm{B}, \rho = x\right)$ for $x > 0$ and $x < \frac{d}{2}$.

Trivially, $\Pr\left(\mathrm{B} \middle| \rho = x\right)$ equals

$$\Pr\left(\mathrm{B} \middle| \rho = x\right) = (1 - e^{-\lambda_2 \Delta(x,d)}).$$

Now we calculate the conditional probability of A given B and ρ. The conditional probability can be written as:

$$\Pr\left(\mathrm{A} | \mathrm{B}, \rho = x\right) = \frac{1}{\Pr\left(\mathrm{B} | \rho = x\right)} \left(\int_0^{\Delta(x,d)} f_\delta(\delta) \int_{\max(0, \delta - \frac{x^2}{2})}^{\infty} f_\alpha(\alpha)\, d\alpha\, d\delta \right),$$

Since we are only considering the case where $x < d/2$, we can write the conditional probability as follows:

$$\Pr\left(\mathrm{A} | \mathrm{B}, \rho = x\right) = \frac{1}{\Pr\left(\mathrm{B} | \rho = x\right)} \left(\int_0^{\frac{x^2}{2}} f_\delta(\delta) \int_0^{\infty} f_\alpha(\alpha)\, d\alpha\, d\delta + \int_{\frac{x^2}{2}}^{\Delta(x,d)} f_\delta(\delta) \int_{\delta - \frac{x^2}{2}}^{\infty} f_\alpha(\alpha)\, d\alpha\, d\delta \right).$$

Since $\int_0^\infty f_\alpha(\alpha)\,d\alpha = 1$,

$$
\begin{aligned}
\Pr(\mathrm{A}|\,\mathrm{B},\rho = x) &= \frac{1}{\Pr(\mathrm{B}|\,\rho = x)}\left(\int_0^{\frac{x^2}{2}} f_\delta(\delta)\,d\delta + \int_{\frac{x^2}{2}}^{\Delta(x,d)} f_\delta(\delta)\int_{\delta-\frac{x^2}{2}}^{\infty} f_\alpha(\alpha)\,d\alpha\,d\delta\right)\\
&= \frac{1}{\Pr(\mathrm{B}|\,\rho = x)}\left(\int_0^{\frac{x^2}{2}} f_\delta(\delta)\,d\delta + \int_{\frac{x^2}{2}}^{\Delta(x,d)} f_\delta(\delta)e^{-\lambda_3(\delta-\frac{x^2}{2})}\,d\delta\right)\\
&= \frac{1}{\Pr(\mathrm{B}|\,\rho = x)}\left(\int_0^{\frac{x^2}{2}} \lambda_2 e^{-\lambda_2\delta}\,d\delta + \int_{\frac{x^2}{2}}^{\Delta(x,d)} \lambda_2 e^{-(\lambda_2+\lambda_3)\delta}e^{\lambda_3\frac{x^2}{2}}\,d\delta\right)\\
&= \frac{1}{\Pr(\mathrm{B}|\,\rho = x)}\left(\left[-e^{-\lambda_2\delta}\right]_0^{\frac{x^2}{2}} + \left[\frac{-\lambda_2}{(\lambda_2+\lambda_3)}e^{-(\lambda_2+\lambda_3)\delta}e^{\lambda_3\frac{x^2}{2}}\right]_{\frac{x^2}{2}}^{\Delta(x,d)}\right)\\
&= \frac{1}{\Pr(\mathrm{B}|\,\rho = x)}\left((1-e^{-\lambda_2\frac{x^2}{2}}) - \frac{\lambda_2}{(\lambda_2+\lambda_3)}e^{-(\lambda_2+\lambda_3)\Delta(x,d)}e^{\lambda_3\frac{x^2}{2}} + \frac{\lambda_2}{(\lambda_2+\lambda_3)}e^{-(\lambda_2+\lambda_3)\frac{x^2}{2}}e^{\lambda_3\frac{x^2}{2}}\right)\\
&= \frac{1}{\Pr(\mathrm{B}|\,\rho = x)}\left((1-e^{-\lambda_2\frac{x^2}{2}}) + \frac{\lambda_2}{(\lambda_2+\lambda_3)}(e^{-\lambda_2\frac{x^2}{2}} - e^{-(\lambda_2+\lambda_3)\Delta(x,d)}e^{\lambda_3\frac{x^2}{2}})\right)\\
&= \frac{1}{\Pr(\mathrm{B}|\,\rho = x)}\left((1-e^{-\lambda_2\frac{x^2}{2}}) + \frac{\lambda_2}{(\lambda_2+\lambda_3)}(e^{-\lambda_2\frac{x^2}{2}} - e^{-\lambda_2\Delta(x,d)-\lambda_3(\frac{d^2}{2}-xd)})\right).
\end{aligned}
$$

Now using that $\Pr(\mathrm{A}\cap\mathrm{B}|\,\rho = x) = \Pr(\mathrm{A}|\,\mathrm{B},\rho = x)\Pr(\mathrm{B}|\,\rho = x)$, this implies that when $x < \frac{d}{2}$ and $z = 1$,

$$
\Pr\left(\mathrm{A}\cap\mathrm{B}\,\middle|\,\rho = x\right) = (1-e^{-\lambda_2\frac{x^2}{2}}) + \frac{\lambda_2}{(\lambda_2+\lambda_3)}(e^{-\lambda_2\frac{x^2}{2}} - e^{-\lambda_2\ \Delta(x,d)-\lambda_3(\frac{d^2}{2}-xd)}).
$$

and for $x \geq \frac{d}{2}$ and $z = 1$,

$$
\Pr\left(\mathrm{A}\cap\mathrm{B}\,\middle|\,\rho = x\right) = 1 - e^{-\lambda_2\Delta(x,d)}.
$$

Then for the case of $x > 0$ and $x \neq d$ we have

$$\Pr\Big(X=x\Big|z=1,\rho=d,x>0,x\neq d\Big)=\begin{cases}1-e^{-\lambda_2\Delta(x,d)}, & \text{for } x\geq\frac{d}{2}\\ (1-e^{-\lambda_2\frac{x^2}{2}})+\frac{\lambda_2}{(\lambda_2+\lambda_3)}(e^{-\lambda_2\frac{x^2}{2}}-e^{-\lambda_2\Delta(x,d)-\lambda_3(\frac{d^2}{2}-xd)}), & \text{for } x<\frac{d}{2},\end{cases}$$

which we then insert in the probability to donate an amount $x>0,x\neq d$:

$$\begin{aligned}\Pr\Big(X=x\Big|x>0,x\neq d\Big)= &\quad \lambda_1\Pr(\rho=x)+\mathbb{1}_{x\geq\frac{d}{2}}(1-\lambda_1)\Pr(\rho=x)\left[1-e^{-\lambda_2\Delta(x,d)}\right]\\ &+\quad \mathbb{1}_{x<\frac{d}{2}}(1-\lambda_1)\Pr(\rho=x)\left[(1-e^{-\lambda_2\frac{x^2}{2}})+\frac{\lambda_2}{(\lambda_2+\lambda_3)}(e^{-\lambda_2\frac{x^2}{2}}-e^{-\lambda_2\Delta(x,d)-\lambda_3(\frac{d^2}{2}-xd)})\right].\end{aligned}$$

To summarize, we can now insert these cases into the probability to observe a donation x:

$$\begin{aligned}\Pr(X=x) &= \lambda_1\Pr(\rho=x)+(1-\lambda_1)\Big[\Pr(\rho=0)\Pr\Big(X=x\Big|z=1,\rho=0\Big)\\ &+ \Pr(\rho=d)\Pr\Big(X=x\Big|z=1,\rho=d\Big)\\ &+ \sum_{\tilde{\rho}\neq0,\tilde{\rho}\neq d}\Pr(\rho=\tilde{\rho})\Pr\Big(X=x\Big|z=1,\rho=\tilde{\rho}\Big)\Big].\end{aligned}$$

Replacing the $\Pr(\rho=\tilde{\rho})$ with the probability mass function $f(\cdot)$ and using indicator functions for the different cases, the probability that we observe an individual i donating x_i can then be written as

$$\begin{aligned}&\Pr(x_i|d,\lambda,f(\cdot))=\mathbb{1}_{x_i=0}\left\{f(x_i)+(1-\lambda_1)\sum_{\rho>0}^{\frac{d}{2}}f(\rho)\left[\frac{\lambda_3}{(\lambda_3+\lambda_2)}e^{-\lambda_2\frac{\rho^2}{2}}-\frac{\lambda_3}{(\lambda_3+\lambda_2)}e^{-\lambda_3(\frac{d^2}{2}-\rho d)}e^{-\lambda_2\Delta(\rho,d)}\right]\right\}\\ &+\quad \mathbb{1}_{x_i\neq d}\mathbb{1}_{x_i\geq\frac{d}{2}}\mathbb{1}_{x_i\neq0}\left\{f(x_i)\left[\lambda_1+(1-\lambda_1)(1-e^{-\lambda_2\Delta(x_i,d)})\right]\right\}\\ &+\quad \mathbb{1}_{x_i\neq d}\mathbb{1}_{x_i<\frac{d}{2}}\mathbb{1}_{x_i\neq0}\left\{f(x_i)\left[\lambda_1+(1-\lambda_1)\left[(1-e^{-\lambda_2\frac{x_i^2}{2}})+\frac{\lambda_2}{(\lambda_2+\lambda_3)}(e^{-\lambda_2\frac{x_i^2}{2}}-e^{-\lambda_2\Delta(x_i,d)-\lambda_3(\frac{d^2}{2}-x_id)})\right]\right]\right\}\\ &+\quad \mathbb{1}_{x_i=d}\left\{f(x_i)+(1-\lambda_1)\left[\sum_{\rho>0}^{\frac{d}{2}}f(\rho)e^{-\lambda_3(\frac{d^2}{2}-\rho d)}e^{-\lambda_2\Delta(\rho,d)}+\sum_{\rho>\frac{d}{2},\rho\neq d}^{\infty}f(\rho)e^{-\lambda_2\Delta(\rho,d)}\right]\right\}.\end{aligned}$$

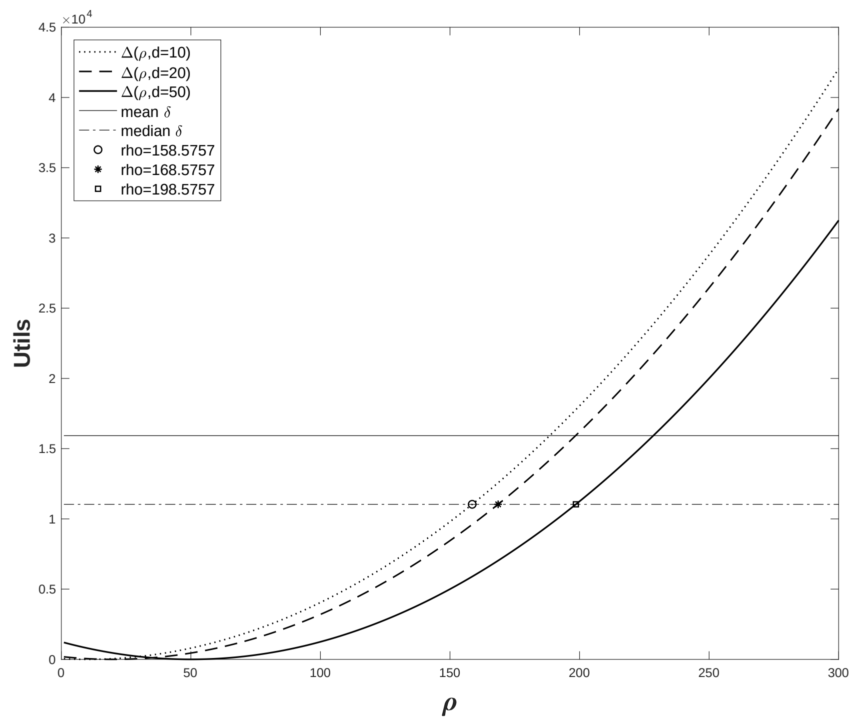

FIGURE D.1. $\Delta(\rho, d)$ versus δ *Notes:* This figure illustrates one of the optimality conditions; it compares the utility gain from donating ρ compared to donating d, which is $\Delta(\rho, d)$ to the estimated mean and median of the opt-out costs distribution of δ. $\Delta(\rho, d)$ is plotted as a function of ρ and the three different default treatments.

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